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Evaluation of Alternative Aptitude Area (AA) Composites and Job Families for Army Classification

Tirso Diaz, Michael Ingerick, and Mary Ann Lightfoot
Human Resources Research Organization

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14. ABSTRACT *(Maximum 200 words)*:

Effective January 2002, the Army adopted a set of nine AA composites based on empirically estimated weights for a seven subtest ASVAB battery. With support from the U.S. Army Research Institute for the Behavioral and Social Sciences (ARI), Zeidner, Johnson, and colleagues developed these composites as part of a proposed two-tiered classification system. This change was motivated by a program of research funded by ARI and conducted by Zeidner, Johnson, and others demonstrating that the proposed system could significantly improve the overall classification and assignment of Army personnel to entry-level jobs.

The current study aimed to independently evaluate the efficacy of the proposed AA composites, and corresponding job families, to meet the Army's classification objectives. More specifically, the present study tested the stability and differential validity of the proposed AA composites and accompanying job families, particularly the 17 and 150 relative to the 9 AAs, and their practical effects on classification efficiency, as measured by mean predicted performance (MPP). For both scientific and practical reasons, the findings suggest the continued operational use of the nine (standardized) AA composites based on the empirically estimated weights developed by Zeidner and colleagues.

15. SUBJECT TERMS

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Evaluation of Alternative Aptitude Area (AA) Composites and Job Families for Army Classification

Tirso Diaz, Michael Ingerick, and Mary Ann Lightfoot
Human Resources Research Organization

Selection and Assignment Research Unit
Michael G. Rumsey, Chief

U.S. Army Research Institute for the Behavioral and Social Sciences
2511 Jefferson Davis Highway, Arlington, Virginia 22202-3926

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FOREWORD

Assigning tens of thousands of Army recruits per year to the jobs for which they are best suited and in a way that maximizes aggregate Soldier performance represents a major goal for the Army. The U.S. Army Research Institute for the Behavioral and Social Sciences (ARI) has a long history of conducting and supporting research aimed at improving the Army's selection and classification process. Effective January 2002, the Army adopted a set of nine Aptitude Area (AA) composites, to select and classify recruits into entry-level jobs, utilizing weights derived from Soldier performance data (circa 1989). Relative to the composites they replaced, the new composites are more defensible with their reliance upon actual performance data, and they make use of the entire profile of aptitude information available for each recruit.

The current study aimed to independently evaluate the efficacy of these new composites as well as alternative AA composites to meet the Army's classification objectives. More specifically, the present study tested the stability and relative uniqueness of several alternative AA composite / job family structures, and their practical effects on classification efficiency. For both scientific and practical reasons, the findings recommend the continued operational use of the nine (standardized) AA composites and do not support the use of a larger number of composites / job families. These findings have been briefed to the Enlisted Accessions Division, G-1 and, in effect, represent a pull-back of recommendations based on earlier research for increasing the number of composites/job families.

MICHELLE SAMS
Technical Director

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EVALUATION OF ALTERNATIVE APTITUDE AREA (AA) COMPOSITES AND JOB FAMILIES FOR ARMY CLASSIFICATION

EXECUTIVE SUMMARY

Research Requirement:

To select and classify recruits to jobs, the Army employs nine Aptitude Area (AA) composites. Effective January 2002, the Army adopted a new set of nine AA composites based on empirically estimated regression weights. Developed by Zeidner, Johnson, and colleagues (Zeidner, Johnson, Vladimirsky, & Weldon, 2000, 2001) with support from ARI, these regression-weighted composites were part of a proposed two-tiered classification system designed to substantially enhance the classification potential of the Army's AA composites. In an earlier report (Diaz, Ingerick, & Lightfoot, 2003) we independently replicated Zeidner, Johnson, and colleagues' method of empirically deriving AA composites, including the 9 AA composites currently in operational use. The primary purpose of the current study was to evaluate the efficacy of the proposed AA composites, and corresponding job families, to meet the Army's classification objectives. Specifically, the present study tested the stability and differential validity of the proposed AA composites and accompanying job families, particularly the 17 and 150 relative to the nine AAs, and their practical effects on classification efficiency, as measured by mean predicted performance (MPP).

Method:

To assess the aforementioned issues, we conducted three major sets of analyses. The first set was exploratory and descriptive and aimed to evaluate the stability and reliability of the 9, 17, and 150 composites. The second set was likewise exploratory in nature and focused on assessing the differential validity present in the 9 and 17 test composites. Specifically, these analyses tested between-job differences in both composite validities and predicted performance scores. The third and final set of analyses had two objectives: (1) to jointly assess the practical effects of stability and differential validity on MPP; and (2) to determine the effects of composite estimation method on MPP, and more operationally, on decisions based upon MPP.

Findings:

Overall, our findings supported the continued use of the standardized AA composites based on the 9 job families proposed by Zeidner, Johnson, and colleagues, which are currently in operational use when assigning recruits to entry-level MOS. We recommended these composites over the 17 and 150 AA composites for two reasons. First, consistent with previous research (Zeidner et al., 2003b), moving from 9 to 17 AA composites did not produce a practically significant increment in either overall MPP or MPP by MOS. Second, and more importantly, the 9 AA composites based on standardized weights displayed operationally desirable properties relative to unstandardized composites. Specifically, standardized composites are expected to more effectively balance the optimization of aggregate Soldier performance with the need to satisfy equally important, practical requirements. In conclusion, when coupled with the

administrative costs and other management-related issues associated with changing existing composites / job families and cut scores, the technical and/or practical advantages to adopting the 17 or 150 AA test composites, as currently constructed, are minimal.

Use of Findings:

The present findings, in conjunction with those of the first report (Diaz et al., 2003), support the 9 AA composites currently in operational use.

EVALUATION OF ALTERNATIVE APTITUDE AREA (AA) COMPOSITES AND JOB FAMILIES FOR ARMY CLASSIFICATION

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INTRODUCTION

Background

Aptitude Areas (AA) are critical features of the Army's personnel management system. For more than 50 years, AAs have served two essential functions. First, AAs structure and meaningfully organize entry-level jobs, grouping jobs with similar aptitude requirements into families. These families inform macro-level career field and accession management decisions, with the aim of ensuring a steady pipeline of accessions for fulfilling both short-term and strategic mission requirements. The second function served by AAs is that each defines a tailored composite, which represents a differentially weighted function of aptitudes and skills required for successful performance in a targeted set of jobs. Operationally, these composites produce the scores used to make a wide range of personnel decisions, from setting entry-level cut-scores to matching new recruits to jobs to counseling exiting Soldiers on civilian jobs commensurate with their skills an› ›ilities.

First developed in 1949, AAs have since undergone periodic changes in number and content. From the early 1970s until recently, the Army employed a system of nine AAs. At the core of this system were unit-weighted composites, whose weights (0, 1) were meant to reflect the relative importance of different cognitive aptitudes and abilities (e.g., verbal ability, coding speed, mechanical comprehension) in determining job performance within a family of jobs (e.g., Clerical, Combat, Field Artillery).[1] Starting in January 2002, the Army replaced the unit-weighted composites with a new set of nine AA composites based on empirically estimated regression weights derived from criterion-related validities for the Armed Services Vocational Aptitude Battery (ASVAB) (Greenston, Rumsey, Zeidner, & Johnson, 2001).[2] With support from the Army Research Institute (ARI), Zeidner, Johnson, and colleagues developed the composites as part of a proposed two-tiered classification system intended to replace the existing AAs (see Zeidner, Johnson, Vladimirsky, & Weldon, 2000, 2001). In Zeidner, Johnson, and colleagues' original conceptualization of this system, the first tier was intended for classifying recruits to one of 150 entry-level job families. The second tier, aimed at a smaller set of job families (9 or 17), was meant for vocational counseling, recruiting, and administrative purposes. The proposed two-tiered system was based on a multi-year program of simulation research conducted by Zeidner, Johnson, and others. Results of their research indicated that the proposed two-tiered classification system (and related composites) could produce substantial gains in aggregate Soldier performance over and above that expected using the existing AAs (Johnson, Zeidner, & Leaman, 1992; Statman, 1993; Zeidner et al., 2000, 2001).

Purpose of Report

The current report is the second of two reports documenting research assessing major components of Zeidner and colleagues' proposed two-tiered AA system. The first report (Diaz,

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[1] Unit weights were based on rational linkages to job content made by subject-matter-experts (SMEs).

[2] In descriptions of the Zeidner, Johnson, and colleagues' method, these weights are frequently referred to as least squares estimates (LSE) or LSE weights, as the weights are empirically estimated using conventional ordinary least-squares (OLS) regression.

Ingerick, & Lightfoot, 2004) independently replicated the Zeidner, Johnson, and colleagues' method of empirically deriving AA composites, including the nine AA composites currently in operational use. The primary purpose of this second report is to summarize research evaluating the efficacy of the proposed AA system to meet the Army's classification objectives. More specifically, the goals of this research were to:

1. Evaluate the stability and classification potential of the proposed AA composites, particularly the 17 and 150 relative to the 9 AAs.
2. Evaluate the proposed job family structures comprising the two-tiered system (9, 17, and 150), including the potential identification of alternative job family structures displaying greater classification efficiency.
3. Review remaining issues related to implementing the proposed system.

In summary, the current research aimed to appraise both the process and products (i.e., Pearlman, 1980) of the proposed AA system and its potential for operationally achieving Army classification objectives. In keeping with this goal and the recommendations of other classification researchers (Pearlman, 1980; Sackett, 1988), we placed special emphasis on external and practical criteria, specifically classification efficiency, when evaluating the system.

This report is organized as follows. First, we review the underlying conceptual basis and describe the major components of Zeidner, Johnson, and colleagues' proposed system, and its current operational version. Second, we summarize and discuss our results from a preliminary investigation of: (a) the stability of the proposed regression-weighted AA composites; and (b) the differential validity of the proposed job family structures (9, 17, and 150). Both composite-test stability and the differential validity of proposed job families have implications for the classification potential of the proposed two-tiered system. Third, we summarize our findings from a comprehensive, empirical analysis designed to integrate these two issues. Specifically, this joint analysis assesses the effects of composite stability and differential validity on the classification efficiency of the proposed AA system.[3] Fourth, and finally, we conclude the report with a brief review of major findings, a discussion of remaining implementation issues, and suggestions for future research.

[3] Consistent with Zeidner, Johnson, and colleagues, classification efficiency is measured using standardized mean predicted performance (MPP). MPP is an index of the average predicted job performance of *n* recruits expressed in standard deviation units (i.e., an average z-score).

OVERVIEW OF ZEIDNER, JOHNSON, AND COLLEAGUES' PROPOSED TWO-TIERED CLASSIFICATION SYSTEM

The underlying conceptual basis for Zeidner, Johnson, and colleagues' proposed classification system comes from Differential Assignment Theory (DAT) (Zeidner & Johnson, 1994; Zeidner, Johnson, & Scholarios, 1997). Originating with research by Horst (1954, 1955) and Brogden (1959), DAT makes two fundamental propositions. First, consistent with specific aptitude theories of intelligence, DAT postulates that people and jobs can be differentiated on the basis of specific aptitudes and abilities. Second, DAT emphasizes that within a multiple job context, such as Army classification and assignment, increasing differential validity, as opposed to incremental validity, maximizes classification efficiency. Factors that influence differential validity, and indices of differential validity, include: (a) the number of jobs (m) to which individuals can be assigned: (b) the average predictive (or criterion-related) validity of those jobs (R); and (c) intercorrelations among test composites predicting performance in those jobs (r) (Brogden, 1959; Zeidner & Johnson, 1994; Zeidner et al., 1997). Taken together, DAT posits that when assigning individuals to multiple jobs, performance for the group (as a whole) will be optimized by using a multidimensional test battery and a set of differentially-weighted composites tailored to specific job(s). The practice of matching individual skills and task requirements also has a long, informal history. The designation of the best throwers as "pitchers" in Little League, and the best catchers as "basemen", is one common example of this practice.

Using DAT as a basis, and building on a multi-year program of research, Zeidner and colleagues proposed a two-tiered classification system (see Greenston et al., 2001; Zeidner et al., 2000, 2001). The two-tiered system consists of two major components: (a) differentially-weighted test composites tailored to specific jobs (or job families); and (b) groupings of jobs with comparable aptitude and performance requirements into families or Aptitude Areas (AAs). Each tier encompasses both components. As originally conceived, the first tier was intended for classifying recruits to one of 150 entry-level job families. The second tier, aimed at a smaller set of job families (9 or 17), was meant for vocational counseling, recruiting, and administrative purposes.

Based on their intended purpose, classification or counseling, test composites are estimated differently. When estimating composites, weights are derived from predictive (or criterion-related) validities corrected for range restriction and criterion unreliability. Depending on the tier and the intended use of scores based on the composites, the appropriate reference population (i.e., Youth or Army Input) for making these corrections differs.[4] For instance, corrections to the Youth population are appropriate when scores are used to determine the mental eligibility of high school seniors for Army service. Conversely, corrections to the Army Input population are most appropriate when using scores to assign recruits to entry-level jobs. In sum, the specific estimation procedure employed when deriving the weights depends on the types of decisions for which scores based on the composites are intended to support.

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[4] The Youth population represents all 18 – 23 year olds in the U.S. population. The Army Input population represents all Army recruits who pass basic service qualifications, and are therefore, eligible for assignment to entry-level MOS.

The "operational" version of the proposed two-tiered system functions somewhat differently than the version originally proposed by Zeidner and colleagues. The primary difference is that under this system, *both* tiers, instead of just the first tier, are used in classifying recruits to entry-level MOS. Specifically, the second tier, consisting of either 9 (or 17) AAs and corresponding test composites, is used to determine a recruit's eligibility for assignment to an MOS. Consequently, these composites, and their respective weights, are referred to as *assignment (AA) composites* (or *AA weights*). The first tier, comprised of 150 job families and corresponding composites, is used for estimating a recruit's predicted performance.[5] First tier composites, and their respective weights, are referred to as *predicted performance (PP) composites* (or *PP weights*). Predicted performance scores are used operationally, in conjunction with AA scores, to inform decisions as to where to assign recruits, so as to optimize overall aggregate Soldier performance.

Because the primary motivation for the current research is on the AA composites and corresponding job family configurations, our analyses focused on the "operational" version of the Zeidner and colleagues' two-tiered classification system and its efficacy in achieving Army classification objectives.

[5] Those job families making-up the first tier are basically individual-level MOS.

PRELIMINARY INVESTIGATION OF APTITUDE AREA (AA) COMPOSITES AND JOB FAMILY STRUCTURE: ISSUES OF STABILITY AND DIFFERENTIAL VALIDITY

Two long-standing, albeit related, issues regarding the classification potential of regression-weighted test composites are their stability and differential validity. By *stability*, we are referring to the degree to which estimates, in this case OLS-derived regression weights, accurately reflect an underlying population value (i.e., are generally free of sampling error). By *differential validity*, we are referring to between-job family differences in: (a) the predictive (or criterion-related) validities (R) of a test composite; and (b) the degree to which test composites, and their predicted performance scores, are intercorrelated (r).[6] In a classification context, differential validity is maximized when predictive validities differ by family and the intercorrelations among test composites are low. More importantly, when making operational decisions about the classification potential of one or more test composites, these differences should be attributable to systematic between-family differences in job content and performance requirements and *not* other extenuating factors such as estimation (i.e., sampling) or measurement error.

While the implications of sampling error on personnel selection decisions are well-known in applied psychology (Hunter & Schmidt, 1990; Schmidt & Hunter, 1977), there is comparatively less attention to this issue as it pertains to classification. In the context of classification, sampling error can lead to inaccurate composite estimates, which in turn may artificially inflate (or deflate) estimates of differential validity. Practically, this means that jobs may appear to be more or less different than they actually are. When making operational decisions, this instability is likely to bias estimates of a composite's classification potential, as measures of classification effectiveness, such as mean predicted performance (MPP) are typically based on one or more indices of differential validity (see Brogden, 1959; Zeidner et al., 1997). That is, the higher the differential validity across a set of jobs, the greater will be the estimated classification potential of a set of composites specifically tailored to those jobs. However, if estimates of differential validity are biased (positively or negatively) leading to inaccurate estimates of classification potential, then decisions regarding the operational utility of a set of composites will be adversely affected. Presently, there is a long-standing debate about the degree to which regression-weighted composites tailored to specific jobs based on test batteries assessing specialized aptitudes and abilities, such as the ASVAB, produce differences in validities that represent "true" between-job differences and not differences due to sampling error or other artifacts (Hunter, 1983, 1985; Hunter, Crosson, & Friedman, 1985; Schmidt, Hunter, & Larson, 1988; Schmidt, Hunter, & Pearlman, 1981; Zeidner & Johnson, 1994; Zeidner et al., 1997).

As an initial step in evaluating the proposed AA system, we first investigated these issues. In addition to rationally examining the methods for deriving the composites and job family structures, we conducted several exploratory analyses designed to answer the following questions:

1. To what extent are both the individual regression weights making up the composites, and the composites (as a whole), stable and largely free of sampling error?

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[6] Differential *validity* is synonymous with differential *prediction*.

2. Since test composites are tailored to specific job families, to what degree do composites differ across the proposed job family configurations? That is, is there differential validity? If not, are there alternative job family configurations that might increase differential validity and, thereby, classification efficiency?

We will summarize our findings for each in turn.

Stability of Proposed Aptitude Area (AA) Composites

In an earlier report (see Diaz et al., 2004), we successfully replicated Zeidner, Johnson, and colleagues' method for estimating the proposed OLS-weighted composites. In this section, we evaluate the stability of those weights. The section is organized as follows. First, we briefly review Zeidner and colleagues' method for deriving the proposed AA composites, noting its implications for composite stability and more practically, classification efficiency. Second, we summarize our findings from a series of exploratory analyses aimed at empirically assessing the stability of the proposed test composites.

Overview of Zeidner and Colleagues' Method for Deriving Regression-Weighted AA Composites

In general, Zeidner and colleagues' method involves estimating weights from corrected ASVAB intercorrelations and criterion-related validities using standard OLS regression.[7] All weights are job- or AA-specific, meaning that weights are estimated separately for each MOS or a family of MOS with comparable job requirements to produce composites targeted to that specific MOS (or job family). In accordance with Differential Assignment Theory (DAT), empirically-estimated weights are expected to differ across jobs (i.e., exhibit differential validity) in meaningful ways that capture systematic job-to-job differences in content and performance requirements, just as the unit-weighted composites did with dichotomously assigned weights (0,1) based on a rational analysis of job requirements. As a result, MOS-specific composites should differentially predict Soldier performance for that MOS (or job family).

Using this approach, Zeidner and colleagues derived two sets of regression-weighted test composites for use under the AA system. The first set of test composites, and their respective weights, is intended for computing AA scores to be used in determining recruit eligibility for assignment to an MOS. These composites constitute the second tier of Zeidner and colleagues' proposed two-tiered classification system. The second set of test composites, and their respective weights, is intended for computing predicted performance scores. Operationally, predicted performance scores inform assignment decisions, in conjunction with the AA scores. These weights form the first tier of the proposed two-tiered classification system. In addition to informing Army classification decisions, these scores have frequently been used by Zeidner and colleagues for basic research purposes when evaluating classification system design issues.

As discussed earlier, regression-weighted composites are potentially problematic for classification purposes because regression-based estimates are sensitive to sampling error

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[7] Correlations are corrected for criterion unreliability and range restriction, as observed correlations are based on predictor-criterion data truncated by selection and classification effects.

(Cohen, Cohen, Aiken, & West, 2003; Pedhauzer, 1997). This means that regression-based estimates are likely to capitalize on sample-specific variance (Hunter et al., 1985; Schmidt et al., 1988). To address this issue, Zeidner and colleagues aggregate jobs (MOS) to ensure sample sizes (*n*s) of 200 or greater when estimating composite weights. Estimates based on this design are expected to be generally free of error (see Zeidner et al., 2000, 2001) and, therefore, representative of the "true", underlying population values.

While the aforementioned procedure should (and likely does) decrease estimation error, there are several reasons for investigating this issue more thoroughly. First, many of the sample sizes (*n*s) on which weights and composites are based, specifically those comprising the first-tier, still fall below recommended levels (Maxwell, 2000). While increasing *n* minimizes the standard errors associated with these weights, since error is inversely related to *n*, such increases do not completely eliminate error. This is problematic because even relatively small standard errors can distort conclusions about differential validity. For example, consider two weights for the same predictor for two different jobs, .08 (Job A) versus .11 (Job B). Assuming no error, the weight for Job B is 37.5% larger than that of Job A, suggesting that the attribute underlying the predictor is more important to the performance of Job B than Job A. Given these data, there is evidence for differential validity. Now, assume that the standard error associated with both weights is small, about .02. This means that the "true" weight for Job A is somewhere between .06 and .10, while the "true" weight for Job B is between .09 and .13. Given this new information, the weights now suggest two alternative, but differing, conclusions. The first is that, since there is overlap in the estimates, differential validity is close to zero because the observed difference in the weights is artifactual (i.e., due to error). The second conclusion is that the "true" weights may actually differ *more* than the observed difference suggests, indicating that differential validity is greater, and potentially more than double, that in the original example.[8]

This situation becomes especially problematic when observed weights are close to zero, since once error is taken into account this suggests that the "true" population weights are basically zero; there is no relationship between the predictor in question and job performance. Therefore, any observed differences between these weights and those that are technically non-zero, but otherwise represent small effects, are likely to be misleading. As evident from this illustration, even relatively small standard errors can adversely impact estimates and conclusions about differential validity, and more practically, classification efficiency. A cursory review of the proposed weights and composites, particularly for the first-tier based on a 150 job family configuration, shows that there are many cases: (a) where the observed differences in the weights for the same ASVAB subtest across families is sufficiently small to potentially capitalize on error; and (b) where observed weights are relatively close to zero.

The second reason for further investigating the stability of the test composites is the high level of collinearity present among the predictors, the ASVAB subtests. Collinearity, or in this case multicollinearity, refers to the degree to which a set of predictors correlate with each other.

[8] Note the same issues apply when considering differential validity as it applies to intercorrelations among the composites and corresponding predicted performance scores (*r*). Since correlations are biased due to sampling error, the greater the sampling error, the higher the intercorrelation among predicted performance scores (and the lower the differential validity among the composites).

When multicollinearity is high, standard errors are inflated (Cohen et al., 2003; Pedhauzer, 1997). This produces a condition known as "bouncing betas", whereby the magnitude, and even the direction, of the weights changes depending on which predictors are included in the regression model. Intercorrelations among the ASVAB subtests comprising the current 7-test battery tend to be uniformly high, ranging from .41 to .83 in the Youth population (Mitchell & Hanser, 1984).[9] When working with the Army Input population, intercorrelations among the ASVAB subtests at the MOS- and job family-level are roughly comparable in magnitude. Therefore, the level of multicollinearity present in the ASVAB subtests is likely to contribute to inflated standard errors when estimating composite weights. While increased *n* is associated with smaller standard errors, even large *n* is not expected to fully negate the influence of collinearity on regression-based estimates.

In summary, additional research on test composite stability, and its implications for the proposed classification system, is needed. The sample sizes (*n*) employed during estimation and the multicollinearity present in the ASVAB could not only separately, but also jointly, contribute to inflated standard errors. The magnitude of these errors, even those that are relatively small, is practically important as subsequent conclusions regarding the differential validity of the test composites could be impacted. To address these issues, we conducted a series of exploratory, descriptive analyses to empirically assess the stability of the proposed test composites. All analyses were based on estimates originally derived by Zeidner, Johnson, and colleagues (Zeidner et al., 2000, 2001) and successfully replicated by Diaz et al. (2004). Estimates were based on data contained in the Skills Qualification Test (SQT) program database. This database contains ASVAB subtest scores and standardized Skilled Qualification Test (SQT) scores for Army enlisted personnel covering FYs 1987-1989 ($N = 257{,}810$). These data were originally provided by the U.S. Army Research Institute (ARI).

Results of Exploratory Analyses Describing the Stability of the Proposed Test Composites

To assess the stability of the test composites and their respective weights, we conducted two sets of descriptive analyses. The first looked at the magnitude of the effect sizes associated with the composites and their respective weights to identify "weak" composites, that is composites whose weights were generally not significantly different from zero. More specifically, the purpose of these analyses was to detect test composites that, by virtue of having effect sizes not significantly different from zero, were generally unstable and thereby could be expected to bias estimates of differential validity. The second set of descriptive analyses, signal-to-noise, assessed the effects of collinearity and data truncation on the composites. Comparable to the first set of analyses, the purpose of the signal-to-noise analyses was to identify problematic composites that could substantially bias inferences about differential validity. We will summarize each in turn.

Identifying Weak Composites. For these analyses, we took the estimated composites and their respective weights, specifically the first-tier weights for the 150 job families and the second-tier weights for the 17 and 9 job families, and calculated an applicable significance test.

[9] These intercorrelations are used when making range restriction corrections to ASVAB-criterion validities to estimate the first-tier weights and composites.

For the individual weights, we computed conventional t-tests, estimating the degree to which the observed values were significantly different from zero. For the full composites, we conducted chi-square tests of significance estimating the degree to which the test composite (as a whole) differed from zero.[10] When conducting the tests, we considered the standard error of the weight or the composite, respectively. That is, all tests estimated the degree to which observed values were significantly different from zero, taking into account the applicable standard error. This enabled us to distinguish between those weights and composites whose difference from zero was most likely artifactual (due to error) versus those whose effect size was technically small, but otherwise stable. From these analyses, we observed the following.

First, as expected, there was a strong linear relationship between sample size (*n*) and composite stability. Tables 1 and 2 summarize the number (and percentage) of job families exhibiting non-significant weights by job family configuration and ASVAB subtest.[11] As evident from Tables 1 and 2, as the number of job families increased, and thereby *n* decreased, the number of non-significant weights, controlling for error, likewise increased. While the effects of small *n* were minor at the 9 and 17 job family configurations, they were most pronounced for the 150 job family configuration (see Table 2), where for 40.7% of the job families more than half of the weights making-up their respective composite were not significantly different from zero ($p < .05$). As confirmation of this, the relationship between *n* and the number of nonsignificant weights among the 150 job families was strongly negative ($r=-.673$, $p < .0001$, $N = 150$), indicating that as *n* decreases, the number of non-significant weights in a test composite increases. Therefore, while weights for the 9 and 17 job family configurations are reasonably robust (i.e., significantly different from zero), this was not the case for a sizeable percentage of the 150 job families.

Table 1
Number (and Percentage) of Job Families with Non-Significant Weights and Composites by ASVAB Subtest and Job Family Configuration

	GS	AR	AS	MK	MC	EI	VE	Full Composite
JF	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)
9	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)
17	5(29.4)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	1(5.9)	0(0.0)	0(0.0)
150	119(79.3)	33(22.0)	46(30.7)	31(20.7)	74(49.3)	76(50.7)	67(44.7)	0(0.0)

Note. For the 9 and 17 job family configurations, results exclude weights fixed to zero because of positive constraint. Significance set at $p < .05$ (two-tailed). GS = General Science; AR = Arithmetic Reasoning; AS = Auto & Shop Information; MK = Mathematical Knowledge; MC = Mechanical Comprehension; EI = Electronics Information; VE = Verbal.

[10] Given the *n* involved, these chi-square tests are equivalent to the standard overall *F*-test in regression.
[11] For significance tests results by job family and ASVAB subtest, see Appendix A.

Table 2
Number (and Percentage) of Job Families with Non-Significant Weights within their Respective Composite by Job Family Configuration

	Number of Non-Significant Weights						
	0	1	2	3	4	5	6
JF	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)	*N*(%)
9	9(100.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)
17	12(70.6)	4(23.5)	1(5.9)	0(0.0)	0(0.0)	0(0.0)	0(0.0)
150	7(4.7)	21(14.0)	29(19.3)	32(21.3)	40(26.7)	16(10.7)	5(3.3)

Note. For the 9 and 17 job family configurations, results exclude weights fixed to zero because of positive constraint. Significance set at $p < .05$ (two-tailed).

The second trend is that composite stability was related, over and above the effects of *n*, to the particular ASVAB subtest and job family. As can be seen from Table 1, the GS subtest was consistently associated with small effect sizes, particularly at the 150 job family configuration, where 79.3% of the job families displayed a non-significant weight for GS. Inspection of the actual weights confirmed this, as GS repeatedly corresponded to lower effect sizes relative to the other subtests, even when weights were technically significant. At the 150 job family configuration, EI (50.7% non-significant), MC (49.3%), and VE (44.7%) also emerged as ASVAB subtests that tended to be associated with non-significant effect sizes. This suggests that: (a) the ability of some subtests to differentiate among the job families (as currently constructed) is minor; and (b) some of the observed differentiation for a large number of families at the 150 level is largely artifactual (due to error). As for individual job families, a visual inspection of plots, showing the standard errors of composite weights organized by *n* and ASVAB subtest for the 150 job family configuration, indicated that the magnitude of the error varied among job families with comparable *n*. That is, holding *n* and ASVAB subtest constant, some job families were associated with larger standard errors than others. This indicates that sampling error differentially affected composite estimates for the different job families, as would be expected given that the effects of sampling error are random.

In sum, we identified a number of composites, mainly at the 150 job family configuration, that are weak. That is, controlling for error, there were a number of composites containing weights that were not significantly different from zero. Larger standard errors tended to be a function of: (a) low *n*; (b) the ASVAB subtest corresponding to the weight; and/or (c) sampling error. These findings are practically important for two reasons. First, they indicate that for a number of families at the 150-level there are few ASVAB subtests to meaningfully differentiate them from other jobs. Second, because of the number of composites that are weak, estimates of differential validity, particularly for those weights relatively close to zero, will either over- or under-estimate "true" differences between job families.

Signal to Noise. We also conducted diagnostics to examine the impact of collinearity among ASVAB tests on the quality of the estimated weights of the composites using the approached described by Belsley (1988). This approach employs a signal-to-noise measure that jointly accounts for two sources of "weakness" in the data, namely, collinearity and "short data." In our diagnostics, the "signal" corresponds to the unknown population values of the composite LSE weights, while noise corresponds to error in estimating these weights. Collinearity and/or

short data can lead to unstable regression weights and are directly relevant in our problem. First, the high correlations among ASVAB scores raise concerns regarding the potentially adverse effects of collinearity on the composite weights.[12] Second, restriction in range due to sample selection is relevant to the problem of short data, which occurs when a predictor has small length (or variance).[13] ASVAB tests that are important to the job family or MOS potentially exhibit short data problem since they are impacted most by selection-related range restriction, with estimated weights with the "wrong" sign.

The following steps summarize the "weak data" diagnostic framework of Belsley (1991), as it applies to the current problem. These diagnostic steps are carried out separately at the MOS- or job family- level data. In the descriptions below, X denotes the n by seven matrix of ASVAB test scores of individuals belonging to the MOS or job family under consideration.

1. *Detecting Collinearity Problem.* The collinearity diagnostic is based on the indices

$$\eta_k = \frac{\mu_7}{\mu_k}, k = 1,2,\ldots,7$$

   where μ_k is the *k*th smallest singular value of X (or square-root of the kth smallest eigenvalue of X'X) and μ_7 is the maximum singular value of X. A collinearity problem exists if the largest index η_1 is greater than 30. Note that the cut-off value 30 is the same as that typically used when identifying important dimensions in factor analysis. The number of linear dependencies (or dimension of the collinearity problem) is equal to the number of values greater than 30. Two or more subtests are involved in a linear dependency if the variances of their regression weight estimates are mostly accounted for by the same linear dependency.

   While collinearity can be expected to degrade regression weight estimates of subtests that are involved in the relevant linear dependencies, by itself it is not harmful. If there is a strong enough relationship between job performance criterion and ASVAB subtests, then the regression weight estimates would still be reliable.

2. *Signal-To-Noise Diagnostic.* The signal-to-noise diagnostic is conceptually based on

$$\tau^2 = \beta^T \left[\mathrm{var}(\hat{\beta})\right]^{-1} \beta$$

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[12] A distinction is made in this approach between collinearity and correlation or statistical relationship in general. Correlation is sufficient but not necessary for collinearity. A collinearity problem is characterized by near "linear dependence" among two or more predictor variables. Geometrically, these predictors form an unstable base for the regression expectation surface, which can lead to unstable weights.

[13] Correction for range restriction that is traditionally applied to adjust selection sample correlations to a reference population values does not address the short data problem. While these two issues are not exactly equivalent, they are related. Under the same condition, when the range of a subtest is restricted, the small variance in the subtest leads to "difficulty" in estimating the subtest weight.

where β is the true but unknown regression weight and $\hat{\beta}$ is the estimate of the regression weight with variance $\mathrm{var}(\hat{\beta})$.[14] Computationally, the diagnostic is carried out using a test statistic, based entirely on the LSE estimate $\hat{\beta}$, that is distributed as a non-central F (see equation (7.12) on page 212 of Belsley). Conceptually, large values of the ratio τ^2 (and the test statistic) indicate that there is a sufficient signal-to-noise ratio. This arises when the unknown regression weight β is large enough, even if the variance $\mathrm{var}(\hat{\beta})$ is inflated due to collinearity problems; large enough values also could arise even if β is small (e.g., weak criterion-subtest relationship) if the corresponding predictor variable is not involved in a collinearity problem with small $\mathrm{var}(\hat{\beta})$.

The combination of the collinearity diagnostic index and the signal-to-noise ratio triangulates the weak data problem in the following way. First, there is no weak data problem if the signal-to-noise ratio is significantly high, even in the presence of linear dependencies (i.e., η_k values above 30). Collinearities in this situation are considered not harmful. Second, if the signal-to-noise ratio is not significant, then this indicates one of two weak data problems: (1) harmful collinearity, in the presence of linear dependencies; (2) or short data, in the absence of linear dependencies. This triangulation is summarized in the table below:

		Presence of collinearity as indicated by collinearity diagnostic	
		NO	**YES**
Inadequacy of signal-to-noise diagnostic	**NO**	No weak data problem	Not harmful collinearity
	YES	Short data problem	Harmful collinearity problem

In summary, data weakness in the job performance equation estimation potentially arises from "correlated" predictor ASVAB battery and "data shortness" (or range restriction) due to sample selection. If weak data is detected then there is not enough information (or power) in the sample to conclude one way or another regarding significance or the nature of the relationship between a subtest and job performance and a larger sample may be required.

Results of Weak Data Diagnostics. Table 3 summarizes the results of the weak data diagnostic analysis in terms of number of ASVAB subtests involved in harmful collinearity and short data problem by job family configuration.[15] Overall the result of this analysis is comparable to the stability analyses above based on the usual statistical significance test on each weight. The signal-to-noise test is similar in nature to analysis of power and does not exhibit the tendency of the ordinary significance test to reject the null hypothesis of zero weight when the sample size is sufficiently large.

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[14] Note that this is not the same as the usual test of significance as the unknown parameter value β instead of $\hat{\beta}$ appears in the numerator.

The weak data diagnostics indicate that the overall quality of the 9 job family weights is good. Only GS exhibited weights that were adversely affected by collinearity or short data. Our analysis showed that GS was consistently involved in a linear dependency with VE in five out of nine job families, and AR with MK in eight out of nine job families. However, the sample sizes at the 9 job family configuration and ASVAB-criterion relationship were large enough to overcome harmful effects of collinearity and produce composite weights that could be reliably differentiated from noise.

Table 3
Number (and Percentage) of Job Families with Weights Involved in Harmful Collinearity (HC) and Short Data (SD) Problem by ASVAB Subtest and Job Family Configuration

No. JF	Type of Weak Data	GS N (%)	AR N (%)	AS N (%)	MK N (%)	MC N (%)	EI N (%)	VE N (%)	Total N (%)
9	HC	4 (44.4)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	4 (6.3)
	SD	3 (33.3)	0 (0)	0 (0)	0 (0)	0 (0)	1 (11.1)	0 (0)	4 (6.3)
	Total	7 (77.8)	0 (0)	0 (0)	0 (0)	0 (0)	1 (11.1)	0 (0)	8 (12.7)
17	HC	7 (41.2)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	2 (11.8)	9 (7.6)
	SD	7 (41.2)	0 (0)	2 (11.8)	0 (0)	2 (11.8)	5 (29.4)	0 (0)	16 (13.4)
	Total	14 (82.4)	0 (0)	2 (11.8)	0 (0)	2 (11.8)	5 (29.4)	2 (11.8)	25 (21)
155	HC	93 (60)	52 (33.5)	4 (2.6)	44 (28.4)	1 (0.6)	3 (1.9)	72 (46.5)	269 (24.8)
	SD	59 (38.1)	33 (21.3)	88 (56.8)	31 (20)	115 (74.2)	126 (81.3)	27 (17.4)	479 (44.1)
	Total	152 (98.1)	85 (54.8)	92 (59.4)	75 (48.4)	116 (74.8)	129 (83.2)	99 (63.9)	748 (68.9)

Note. GS = General Science; AR = Arithmetic Reasoning; AS = Auto & Shop Information; MK = Mathematical Knowledge; MC = Mechanical Comprehension; EI = Electronics Information; VE = Verbal.

For the 17 job family configuration, the diagnostics again suggest good quality of weights overall. As in the 9 job family, the GS weights were the most adversely affected by weak data problems, with 14 out of 17 composite weights exhibiting harmful collinearity or short data. Only two additional composites, CL1 and ST2, showed weak data problems on two ASVAB subtests, AS and MC, which previously were not identified under the nine job family. The weak data diagnostics is suggesting that the subtest-criterion relationship for AS and MC simply were not strong enough in CL1 and ST2 jobs, and that under ASVAB collinearity conditions these two subtests do not play an important role for these jobs. Composite weights on the other subtests could be reliably differentiated from noise, even if some of them were involved in linear dependencies (e.g., AR and MK in 14 out of 17 job families).

Diagnostics at the MOS level, which should closely approximate the 150 job family configuration, indicate weak data problems for many MOS-job families and far more ASVAB subtests than observed in the 9 and 17 job family configurations. GS weights continued to exhibit weak data problems for almost all MOS at this level, which is not surprising given earlier observations. However, all the other subtests now exhibit weak data problems for at least 48 percent of the MOS. In particular, AR and MK weights are now susceptible to the linear dependency between these two subtests, while before there was large enough sample size to overcome harmful effects of collinearity for these two subtests. The same can be observed for the other ASVAB collinearities. Overall, the number of subtests that cannot reliably be

differentiated from noise for each MOS-job family, combined with the frequency of this occurrence across MOS-job families, indicate that true differential validity cannot be achieved at the MOS level; that is, many of the MOS-job families will have the same ASVAB validity pattern if we exclude subtests on each MOS-job families that are not different from noise.

In summary, the weak data diagnostics indicate that composite weights at the nine and 17 job family can reliably be differentiated from noise overall. The harmful effects of ASVAB collinearity, while degrading the quality of some of the weights, were not strong enough to conclude that the differential validities and related classification properties of the composite weights are of no value. The situation is very different, however, at the 155 MOS level, where the high frequency of MOS-job family composites with weak composite weights on several subtests at the same time indicates that true differential validity is not achievable at the 155 MOS or 150 job family configuration.

Differential Validity of Proposed Job Family Structure

As described earlier, differential validity is operationalized as between-job differences in ASVAB-predictive (or criterion-related) validities (R), and as between-job differences in intercorrelations among test composites and their respective predicted performance scores (r). For differential validity to be meaningful, these differences need to reflect systematic differences in the underlying performance requirements among the different jobs. Theoretically, differential validity is expected to increase when jobs (or job families) are substantially different from each other in terms of their actual performance requirements. As described earlier, composites are job family-specific in that each composite seeks to maximize performance prediction for that particular MOS or family of MOS. Therefore, how job families are constructed could significantly influence the ability of the composites to differentiate between recruits' expected performance across a family of jobs. In this section, we evaluate between-family differences in the proposed composites, and their respective weights. The section is organized as follows. First, we briefly review Zeidner and colleagues' method for constructing the proposed job families, noting its implications for differential validity, and more practically, classification efficiency. Second, we summarize our findings from a series of exploratory analyses designed to assess the degree to which the job families, as currently constructed, can be meaningfully differentiated using the proposed composites.

Overview of Zeidner and Colleagues' Method for Constructing Job Families

There are a number of different methods available for clustering jobs. Zeidner and colleagues' method represents a hybrid approach. In brief, it involves clustering MOS into families empirically using the previously derived test composites. Using conventional cluster analysis procedures, MOS are allocated to families in a way that minimizes *within*-family differences in composites, while maximizing *between*-family differences. For practical and conceptual reasons, some modifications are then made to the placement of MOS within families based on a rational analysis of job content. This method has produced three alternative configurations of job families. The first consists of 150 job families, the majority of which are individual MOS. This configuration corresponds to the first-tier in Zeidner and colleagues' proposed classification system. The second and third configurations consist of 17 and 9 job families respectively, each family consisting of a

group of comparable MOS. These two configurations represent alternative versions of the second-tier of the proposed classification system.

As with the composites, Zeidner and colleagues' method is motivated by the proposition that jobs differ in the kinds of cognitive aptitudes and abilities required for successful performance. Theoretically, jobs can then be scaled accordingly. There is both empirical and conceptual support for this proposition in applied psychology, which demonstrates that jobs can be differentiated by cognitive ability, including specific aptitudes (DesMaris & Sackett, 1993; Gottfredson, 1986). Equally as important, there is evidence that differences in job requirements are tied to differences in validity. Specifically, jobs requiring higher levels of an aptitude display higher levels of predictive (or criterion-related) validity for that aptitude (Hunter & Hunter, 1984). Therefore, there is good reason to expect that jobs can be: (a) meaningfully differentiated by aptitude; and (b) that said differences will correspond to differences in predictive validity. Nevertheless, additional research on the proposed job family configurations is needed. There are several reasons for this.

The first reason is that clustering MOS into families empirically based on differences in test composites, and their respective weights, potentially capitalizes on error associated with the composites. As described and documented in the preceding section, there is instability in the composites, and their respective weights, particularly at the 150 level. Because of this error, jobs may appear more or less similar than they actually are. Using composites, then, to cluster jobs may lead to misleading recommendations about where to best place MOS within job families, as a means to maximize differential validity and ultimately classification efficiency.

A second reason, not unrelated to the first, is that clustering algorithms are prone to capitalize on sample-specific variance (or error). That is, it is not uncommon for job cluster solutions to fail to cross-validate when using a different sample and/or types of job-related data than that from which the original solution was derived (Pearlman, 1980; Sackett, 1988; Statman, Gribben, Harris, & Hoffman, 1994). In the first place, clustering algorithms depend heavily on internal criteria, specifically some mathematical expression of observed differences relative to other differences within the same data. Equally problematic, different algorithms use different criteria. This explains why different clustering algorithms tend to produce widely divergent job structures, even when using the same data (Lightfoot, Diaz, & Vladimirsky, 1997; Statman et al., 1994). Consequently, results can and do vary from sample to sample owing to the idiosyncrasies within a particular sample. In the second place, clustering techniques, such as that applied by Zeidner and colleagues, typically lack formal statistical significance testing frameworks or "rules of thumb" for determining the reliability and practical significance of observed differences (Lightfoot et al., 1997). In other words, the procedures are primarily exploratory. Therefore, unlike other conventional statistical methods (i.e., regression), there are no guides for minimizing Type I or Type II errors as is common in conventional hypothesis testing.

In summary, while there is some basis to expect that the proposed job families will be associated with between-family differences in the composites, additional research is needed. Specifically, the current analyses were motivated by: (a) the sampling error present in the composites, and their respective weights; and (b) the potential for empirically-driven clustering techniques to capitalize on this error. As before, the magnitude of these errors, even those that are relatively small, is important. Statistically, error could influence estimates and conclusions regarding the differential validity of the composites. Practically, these conclusions could in turn

impact operational decisions about which job family configuration is optimal for classification purposes. Therefore, the effectiveness of Army classification policy is directly tied to the quality of the evidence used to form the conclusions informing these decisions. To address these issues, we conducted a series of exploratory, descriptive analyses aimed at empirically assessing the differential validity of the proposed job families.

Results of Exploratory Analyses Assessing the Differential Validity of the Proposed Job Families

We conducted two sets of descriptive analyses to assess the degree job families (as currently constructed) could be meaningfully differentiated by the proposed test composites. The first analyses directly targeted between-family differences, controlling for sampling error, in the composites and their respective weights within the 9 and 17 job family configurations. That is, the first set of analyses focused on between-family differences in predictive (or criterion-related) validities. The second set of analyses investigated between-family differences in predicted performance scores based on the test composites for the 9 and 17 job family configurations. That is, the second set of analyses focused on the degree to which test composites were intercorrelated, such that they produced predicted performance scores that were generally equivalent across job families.

Differences in Test Composites and their Individual Weights. To directly test differences in the profile of weights making up a composite and different weights individually, we conducted a nested multiple analysis of covariance (MANCOVA) followed-up by individual analyses of covariance (ANCOVAs). For the MANCOVA, job family configuration served as the independent variables and weights for the 7 ASVAB subtests as the dependent variables.[16] To take into account estimation error, we included the square root of observed n (on which estimates were based) as the covariate. To ensure that weights, when aggregated to job family-level, reflected values observed at that level, estimates were weighted by acquisition ns – the same ns used to aggregate validities to the job family-level when originally deriving weights for the 9 and 17 job family configurations. Overall results for the MANCOVAs were meant to test between-family differences, holding error constant, in the profile of weights (i.e., the full equation) comprising the composite. That is, how much of the variability in a linear profile of the weights can be explained by between-family differences? To test between-family differences in specific weights associated with the different ASVAB subtests, we followed the MANCOVA with individual ANCOVAs based on the same model; except for each ANCOVA there was now only one dependent variable, that being the weights for the applicable ASVAB subtest. This two-stage procedure is consistent with recommendations for conducting multivariate tests of differences in multiple dependent variables (Tabachnick & Fidell, 1996).

Results for the omnibus tests in MANCOVA showed that, controlling for sampling error (i.e., $\sqrt{n}$), there were significant between-family differences in the profiles of the weights across job families for both the 9 (Wilk's $\Lambda_{(56,710.768)} = .389, p < .001$) and 17 (Wilk's $\Lambda_{(56,710.768)} = .101, p < .001$) job family configurations. That is, for both the 9 and 17 job family configurations, between-family differences explained a significant amount of the variability in

[15] The model is nested in that the job families comprising the 17 job family configuration are nested within the 9 family configuration.

the profile of the weights, beyond that expected by within-family differences (i.e., random error). At the level of the ASVAB subtests, we observed the following. First, that particular subtests were more strongly associated with between-family differences than others (see Table 4). For example, looking across the two configurations, between-family differences accounted for the greatest variability (see R^2 values) in weights for Auto & Shop Information (AS), Arithmetic Reasoning (AR), and Verbal (VE). Second, the partial effect sizes (R^2s) for the 17 job family

Table 4
Results of Individual ANCOVAs by ASVAB Subtest and Job Family Configuration

	Job Family Configuration							
	9				17			
Subtest	*F*	*df*	*p*	R^2	*F*	*df*	*p*	R^2
GS	5.063	8,137	.001	.228	.950	8,137	.478	.053
AR	13.076	8,137	.001	.433	3.224	8,137	.002	.158
AS	23.875	8,137	.001	.582	4.122	8,137	.001	.194
MK	7.159	8,137	.001	.295	2.530	8,137	.013	.129
MC	7.202	8,137	.001	.296	1.763	8,137	.090	.093
EI	6.191	8,137	.001	.266	2.584	8,137	.012	.131
VE	9.681	8,137	.001	.361	4.297	8,137	.001	.201

Note. R^2 values are partial R^2s and reflect the *unique* contributions of between-family differences associated with a particular job family configuration to variability in the applicable composite weights. GS = General Science; AR = Arithmetic Reasoning; AS = Auto & Shop Information; MK = Mathematical Knowledge; MC = Mechanical Comprehension; EI = Electronics Information; VE = Verbal.

configuration were smaller (roughly 50%+) than the corresponding values for the 9 job family configuration, indicating most of the differentiation between jobs is attributable to the 9 job families. At an aggregate level, this suggests that expanding the 9 job family configuration to 17 families does further differentiate among some jobs, but it is unclear if that added differentiation is practically significant.

In summary, controlling for sampling error, there are differences in composite weights, both as a set and individually, across job families in the 9 and 17 job family configurations. There were two additional observations of note. First, consistent with earlier findings regarding composite stability, certain ASVAB subtests were more strongly associated with between-family differences than others [i.e., Auto & Shop Information (AS) versus General Science (GS)]. Second, expanding the 9 job family configuration to 17 appears to further meaningfully differentiate among the families, but the degree to which this is practically significant (i.e., leads to substantial increase in MPP) was unclear from the present findings.

Differences in Predicted Performance by Composite. To test between-family differences in predicted performance scores by test composite, we computed distance statistics assessing differences in the predicted performance scores across the range of ability. Mathematically, the "distance" between two composites, indexed by *i* and *j*, is represented by the following formula:

$$\mathrm{var}\left(\hat{Y}_i - \hat{Y}_j\right) = R_i^2 + R_j^2 - 2r_{ij}R_iR_j .$$

As the left-hand-side of the expression indicates, this involved estimating predicted performances based on the two composites for each recruit, and taking the variance of their difference in the recruit population. This distance statistic is a useful diagnostic tool for assessing differential validity-related properties of the composites. Two composites that are more or less parallel (i.e., no differential validity) would yield an intra-person composite difference that is fairly constant in the population, as would be indicated by a variance that is close to zero. On the other hand, if the composites are close to orthogonal, then the variance of their difference would be large. In our analysis, we would prefer composites that are dissimilar from each in the sense that variances of their pairwise differences are relatively large. The aforementioned ideas also are readily verified using the computational formula on the right-hand-side of the expression above. In the regression context, this expression is proportional to the loss in overall R-square when two separate regression equations from two samples with equal sizes are combined. This interpretation is not appropriate given the unequal job family sample sizes, but will be employed after some modifications in our second distance statistic. For the full set of pairwise distance values for the 9 and 17 job family configurations, see Appendix C.

For the 9 job family configuration, on average, the Clerical (CL) ($M_D = 4.147$) and Mechanical Maintenance (MM) ($M_D = 5.738$) job families displayed the largest differences with the other families (see Table 5). Similarly, the largest difference between any two families was 12.442 for CL versus MM. A comparable pattern was observed for the 17 job family configuration. The two families exhibiting the largest differences, on average, were Clerical 1 (CL1) ($M_D = 6.313$) and Mechanical Maintenance 1 (MM1) ($M_D = 7.656$). The largest difference between any two families was associated with CL1 versus MM1 (20.242). Overall, differences were larger, on average, for the 17 job family configuration than the 9 job family configuration.

Table 5
Differences in Predicted Performance Scores by Job Family

Job Family Configuration							
9				17			
JF	M_D	*Min*	*Max*	*JF*	M_D	*Min*	*Max*
CL	4.147	1.168	12.442	CL1	6.313	1.420	20.242
CO	2.410	.264	6.423	CL2	2.392	.529	11.222
EL	1.346	.332	3.912	CO1	4.046	.848	9.740
FA	1.630	.264	5.676	CO2	1.629	.194	6.237
GM	1.827	.325	5.003	EL1	1.652	.204	6.669
MM	5.738	1.946	12.442	EL2	1.508	.242	5.387
OF	1.453	.325	4.010	EL3	2.225	.218	9.674
SC	1.592	.267	6.256	FA	1.906	.195	7.178
ST	1.789	.267	6.510	GM1	3.267	.629	9.673
				GM2	2.095	.194	8.132
				MM1	7.656	2.751	20.242
				MM2	2.212	.492	7.222
				OF	1.746	.204	7.231
				SC	1.638	.339	8.023
				ST1	1.876	.195	8.148
				ST2	3.103	.218	12.012
				ST3	1.765	.284	7.220

Note. Distance values reflect variance of differences between pairs of predicted performance scores multiplied by 100.

Table 6 (below) provides a summary comparison of differences in predicted performance scores across the 9 and 17 job family configurations. This table highlights potential increments (or decrements) in differential validity by shredding-out some of the 9 job families into 17 families. When assessing the gains in differential validity by moving from the 9 to a 17 job family configuration and/or to identify possible alternative job family configurations, we focused on two criteria. The first criterion of interest was whether the between-family differences for the same family at the 17 job family level were consistently larger than the corresponding between-family differences at the 9 job family level. As evident from the table, only General Maintenance (GM), Electronics (EL), and Skilled Technical (ST) appeared to show consistent gains (on average) in differential validity from shredding out their respective families at the 9 family configuration into 2-3 smaller families for the 17 configuration. Results for the other families were mixed. For example, splitting the Clerical (CL) job family into CL1 and CL2 produced a sizeable increment (on average) in differential validity for CL1 (from M_D = 4.147 to 6.313), but a relatively considerable drop for CL2 (from M_D = 4.147 to 2.392). A similar pattern is evident with the Combat (CO) job family.

Table 6
Comparison of Distance Statistics Across 9 and 17 Job Family Configurations

JF	M_D	*% +/-*	*JF*	M_D	*% +/-*
Clerical			**Electronics**		
1. CL (9)	4.147	--	1. EL (9)	1.346	--
2. CL1 vs. CL2 (17)	1.736	-58.14	2. EL1 vs. EL2 (17)	.242	-82.02
3. CL1 vs. Other JFs (17)	6.618	+59.59	3. EL1 vs. EL3 (17)	1.459	+ 8.40
4. CL2 vs. Other JFs (17)	2.436	-41.26	4. EL2 vs. EL3 (17)	1.097	-18.50
Combat			5. EL1 vs. Other JFs (17)	1.767	+31.28
1. CO (9)	2.410	--	6. EL2 vs. Other JFs (17)	1.627	+20.88
2. CO1 vs. CO2 (17)	1.543	-35.98	7. EL3 vs. Other JFs (17)	2.360	+75.33
3. CO1 vs. Other JFs (17)	4.213	+74.81	**Skilled Technical**		
4. CO2 vs. Other JFs (17)	1.635	-32.16	1. ST (9)	1.789	--
General Maintenance			2. ST1 vs. ST2 (17)	2.137	+19.45
1. GM (9)	1.827	--	3. ST1 vs. ST3 (17)	1.189	-33.54
2. GM1 vs. GM2 (17)	2.086	+14.18	4. ST2 vs. ST3 (17)	.685	-61.71
3. GM1 vs. Other JFs (17)	3.345	+83.09	5. ST1 vs. Other JFs (17)	1.906	+ 6.54
4. GM2 vs. Other JFs (17)	2.096	+14.72	6. ST2 vs. Other JFs (17)	3.345	+86.98
Mechanical Maintenance			7. ST3 vs. Other JFs (17)	1.884	+ 5.31
1. MM (9)	5.738	--			
2. MM1 vs. MM2 (17)	3.599	-37.28			
3. MM1 vs. Other JFs (17)	7.926	+38.13			
4. MM2 vs. Other JFs (17)	2.119	-63.07			

Note. As in Table 5, distance values reflect variance of differences between pairs of predicted performance scores multiplied by 100. For each comparison, the applicable job family configuration is in parentheses. % +/- reflects the percentage change (increase or decrease) in distance values going from applicable family in 9 job family configuration to corresponding values representing 17 family configuration. Comparisons involving one job family versus "other JFs", excludes related job families (i.e., CL1 vs. Other JFs, excludes CL2).

The second criterion of interest was whether at the 17 job family level within-family differences were comparable to corresponding between-family differences. That is, all other things being equal, it would be preferable that differences *between* families, on average, were substantially larger than differences *within* related families. This was not consistently the case based on the current analyses. For example, differences between ST1, ST2, and ST3 were not consistently larger than average between-family differences involving one of these three families versus the other families (in the 17 job family configuration). MM1 and MM2 displayed a comparable trend. Conversely, EL1, EL2, and EL3 did exhibit average between-family differences consistently larger than corresponding within-family differences. Overall, of the original 9 job families, only EL and GM satisfied both criteria and represented good candidates for shredding.

As a follow-up analysis to assess the practical importance of these differences, we computed the reduction of "total R-squared" from combining pairs of job families from the 17 job family configuration. By "total R-squared," we are referring to the overall R-squared (or total squared composite validity) in the regression problem represented by the combination of 17 separate LSE problems corresponding to the 17 job family composites. This reduction was computed using the following formula:

$$\Delta R_{ij}^2 = \left(R_i^2 + R_j^2 - 2r_{ij}R_iR_j\right)\left(\frac{n_i n_j}{n_i + n_j}\right)\left(\frac{1}{n}\right)$$

We employed acquisition rather than observed sample sizes for the weights n_i and n_j as the former more appropriately reflect the relative size of the job family in the Army; n is the total acquisition size across 17 job families. Note that the expression inside the first parentheses is just the constant distance statistic formula. The entire expression above is a function of job family size such that a large reduction in R^2 would be expected from combining close to orthogonal composites (as in the constant difference distance statistic) that are associated with large job families. Results are reported in Appendix C (see Table 3).

Overall, the pattern was consistent with those from the analyses above of the variance of differences in predicted performance scores. That is, comparisons previously associated with larger variance of differences in predicted performance scores were associated with bigger drops in R^2 even after taking into account job family sizes. Likewise, those families (i.e., CL1, MM1) that tended to show consistently larger variance in performance score differences displayed bigger decrements in R^2 when combined with one of the other families. For example, as with the previous analysis, the biggest reduction in R^2 across all possible combinations was associated with CL1 and MM1 (.005819). More importantly, the loss in R^2 from combining families that represented shred-outs of families from the 9 job family configuration tended to be small to moderate, ranging from .000043 (EL1 and EL2) to .000928 (CO1 and CO2). The average loss in R^2 corresponding to these shred-outs came to .0003639, which loosely corresponds to a .0191 drop in composite validity (R), suggesting that the average loss in total R^2 was not substantially different than that expected by error.

In summary, the distance analysis indicates varying differences in predicted performance scores between families at both the 9 and 17 job family configurations. Only a few families within each configuration consistently exhibited relatively sizeable differences in predicted performance with the other families. Comparing differences between the 9 and 17 job family

configurations suggested mixed results. Shredding families from the 9 into 2 - 3 smaller families for the 17 job family configuration produced both increments and decrements in (average) differential validity across families. Results observed when investigating the expected reduction in composite validity (ΔR^2) from combining families indicate that these composite differences relatively are not sizeable, as the average drop in composite validity (*R*) was practically small when taking into account error. As a whole, these findings are consistent with previous research showing that test composites, and corresponding predicted performance scores, tend to be highly correlated (Greenston et al., 2001). While the present findings could be used to identify possible alternative configurations other than the proposed 9 and 17 configurations, they suggest that the observed differences are not likely to produce practical differences in aggregate Soldier performance (MPP). The final joint analysis, summarized next, provided a more comprehensive answer to that question.

Evaluating the Practical Effects of Composite Stability and Job Family Structure on Classification Efficiency: An Integrated Analysis

The foregoing analyses demonstrated that: (a) test composites are reasonably stable, except for the 150 job configuration; and (b) there is evidence of differential validity in the test composites, even when controlling for sampling error. Although they suggest implications for classification efficiency, these analyses did not *directly* measure the practical effects of these issues on classification efficiency. To assess the practical effects of these issues, we conducted a comprehensive set of analyses that modeled random variation in test composites induced by empirically estimating the weights. Doing this enabled us to examine its impact on both overall MPP and differences in MPP across and within job families.

This section is organized as follows. First, we discuss the motivations for conducting this analysis. Specifically, we review Zeidner and colleagues' method for estimating MPP and its implications for operational decisions regarding the proposed composites and job families. Second, we briefly describe the method used in the current analysis and its advantages. Third, we summarize our findings from the analysis.

Estimating MPP: Implications for Operational Decisions Involving the Proposed Composites and Job Families

When evaluating which features of a classification system are optimal, it is strongly recommended (see Pearlman, 1980; Sackett, 1988) that special emphasis be placed on external criteria, such as indices of classification efficiency. Consistent with these recommendations, indices, specifically MPP, have been used to inform operational decisions for structuring Army classification systems, such as which job family configuration to adopt to maximize MPP (i.e., Zeidner et al., 2000, 2001, 2003b). However, as with any statistical estimate, the quality of MPP estimates could vary considerably depending on the estimation procedure. Therefore, the quality of these estimates is important, as their impact on the effectiveness of these operational decisions could be substantial.

As described earlier, Zeidner and colleagues' have traditionally employed a double cross-validation design for estimating MPP.[17] In brief, this design involves deriving the two sets of weights (evaluation and assignment) separately using different samples of recruits (generically referred to as Samples A and B, respectively), then applying both sets to a third series of cross- or holdout samples (Sample C). Whereas, assignment weights are used to classify the recruits, the evaluation weights are used to compute predicted performance scores. The predicted performance scores are then averaged across recruits within each cross-sample, and then across all cross-samples (usually 20), to obtain an estimate of overall MPP. This overall estimate of MPP has then been used to evaluate features of Zeidner and colleagues' proposed classification system or possible alternatives, such as the optimal job family configuration (see Greenston et al., 2001; Zeidner et al., 2000, 2003b). The purpose of the double-cross validation design is to model sample-to-sample variability (i.e., sampling error) in MPP, which when averaged across the multiple cross-samples is expected to produce an unbiased estimate of overall MPP. While past research has been instructive, there were aspects that could be constructively extended to more definitively evaluate the classification potential of the proposed test composites and job family configurations.

First, as traditionally applied, the double cross-validation design does not directly model error attributable to the test composites, and their respective weights. Under the double cross-validation design, the test composites are essentially treated as fixed. That is, the composite weights are treated as the unknown ("true") population values, which by definition are free of error. In regression terminology, the double cross-validation design models the *standard error of predicted performance*, but not *the standard error of the composites* (and their respective weights). While the two are related, they technically are not the same. That is, while standard errors in predicted performance are partly a function of errors in the test composites, they are also a function of other random sources of sample-specific variance. Therefore, by excluding error associated with the test composites, the current design likely underestimates the level of error associated with MPP. More recent research by Zeidner and colleagues (Zeidner et al., 2003a) confirms this by documenting that there is variability in predictive validities, and indirectly the composite weights, when based on the evaluation and assignment samples.

A second way in which past research could be extended is that previous studies have tended to focus on overall MPP, arguably at the expense of MPP at the job family- or MOS-level. While overall MPP is informative, practically the MPP of the individual job families (or MOS) is expected to be of equal, if not potentially greater, interest to Army personnel decision-makers for the following reasons. First, some job families may be more central to the Army's mission than others, thus decision-makers are likely to be interested in MPP estimates for specific job families. Second, when evaluating the proposed composites and job families, decision-makers will likewise be interested in how MPP is distributed across the different families, such that the high-performing recruits are not being disproportionately allocated to certain families over others. Reports of MPP at the job family- or MOS-level indicate that there

[16] Zeidner and colleagues more recently introduced a triple cross-validation design for estimating MPP (see Zeidner et al., 2003b). Essentially, it is the same design as described previously, except that participants comprising the evaluation (Sample A) and assignment samples (Sample B) are at one point switched, so as to produce a back- and cross-sample set of MPP estimates. The two sets are then averaged to obtain the final estimate of MPP. This design is comparable, but not equivalent, to the k-fold cross-validation design proposed here, where $k = 2$.

is variability in MPP across jobs, such that some jobs are associated with negative MPP values, whereas others with positive MPP values (Zeidner et al., 2000, 2003b). Third, external criteria, such as MPP, can be instructive when assessing job similarity for purposes of determining differential validity. That is, if two job families are comparable in their composites, differences in MPP can be informative for externally validating the practical significance of these differences. Because some job family-level MPPs will be based on smaller sample sizes (n), even when aggregated across multiple cross-samples, the standard error of MPP for these families will be higher than that for all families (as a whole). Therefore, this error could substantially impact conclusions about between-family differences in MPP.

In summary, while previous research has its strengths and has been informative, there are limitations that could impact operational decisions based on these estimates. Specifically, these limitations are: (a) the double cross-validation design typically employed in past studies does not model error in the test composites, and their respective weights, thereby likely underestimating error in MPP; and (b) past research tends to focus on overall MPP with less attention to MPP at the job family- or MOS-level. To address these issues, we conducted a constructive simulation to model the practical effects of estimation error in the composites on MPP and its implications for optimizing classification using the proposed job families.

Method

For the current analyses, we conducted a constructive simulation with multiple replications using actual ASVAB and performance data from the large-scale SQT database from which the proposed composites and job family configurations were derived. The design of the simulation closely represents an extension of Zeidner and colleagues' double-cross validation design, and involved the following steps.

First, similar to Zeidner and colleagues' design, we randomly assigned individual recruits to one of three types of samples. Specifically, we assigned a subset of the total sample ($n = 5{,}000$) to one of 5 cross-samples of 1,000 each (Sample C), then equally partitioned the remaining recruits ($n \sim 250{,}000$) into an assignment (Sample A) and an evaluation sample (Sample B). For the second step, we estimated the applicable AA and PP composites using the assignment and evaluation samples.[18] Third, we optimized the classification of recruits in each of the cross-samples based on scores computed using the previously derived AA composites and the same allocation percentages reported in Zeidner and colleagues' previous work (see Zeidner et al., 2001). Fourth, after assignment, we computed predicted performance scores for each participant in the cross-samples using the PP composites, likewise previously derived. As with Zeidner and colleagues, to obtain mean predicted performance (MPP) we averaged PP scores across participants within each cross-sample. Fifth, and finally, we repeated the first four steps 49 times to obtain data for 49 replications ($k = 49$). To ensure that the majority of the participants in the total sample contributed data to the cross-samples (Sample C), we initially

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[17] Consistent with Zeidner and colleagues, AA and PP composite weights were based on ASVAB-SQT validities corrected for criterion unreliability and range restriction. As we were interested in the contributions of classification (and not selection) to MPP, validities were corrected to the Army Input population, which represents all recruits qualified to serve in the Army and eligible for assignment to entry-level MOS.

partitioned the entire data into 49 subsamples of 5,000 each.[19] For each of the 49 replications, one of the 49 subsamples served as Sample C. The first four steps are consistent with Zeidner and colleagues' double cross-validation design. The fifth step, replicating the double cross-validation design *k* times, extends Zeidner and colleagues' design, enabling us to: (a) directly model random variation (error) in estimating the AA and PP composite weights; and (b) evaluate the practical effects of this variation when making comparisons involving MPP.[20]

To assess differences by job family configuration and composite weight derivation, we employed a 3 x 2 x 2 design. That is, we repeated the above design 10 times to obtain MPP estimates to evaluate the comparisons of interests. There was one factor reflecting job family configuration and two factors reflecting differences in how the assignment composite weights were estimated. The job family configuration factor had three levels (9, 17, and 150) reflecting the alternative job family configurations for the "operational" two-tiered classification system. As for the two composite estimation factors, one focused on the type of constraint placed when estimating the weights and consisted of two levels: no constraint (i.e., observed OLS weights) versus positive constraint (i.e., weights are constrained to be positive). The second estimation factor dealt with the impact of standardizing the weights to produce scores with equal mean and variance, and was comprised of two levels: unstandardized versus standardized. Consistent with its "operational" implementation, the evaluation weights used in computing individual predicted performance scores were always derived using the 150 job family configuration and unconstrained, OLS-regression weights. Since composite weights for the 150 job family configuration are not constrained to be positive, only the no constraint condition was relevant when estimating MPP for the 150 configuration. The conditions comprising the design are summarized in Table 7 below. The SAS programs for replicating the design, with accompanying documentation, are found in Appendix D.

Table 7
Summary of Conditions in 3 x 2 x 2 Design

	Constraint	
Standardization	No Constraint	Positive Constraint
Unstandardized	▪ 9, 17, and 150 JF Configurations	▪ 9 and 17 JF Configurations
Standardized	▪ 9, 17, and 150 JF Configurations	▪ 9 and 17 JF Configurations

This design offers several advantages. First, as with Zeidner and colleagues, it places emphasis on the *practical* effects of composite stability and job family configuration, specifically classification efficiency (i.e., MPP), and not strictly internal or statistical criteria. Second, the current design extends Zeidner and colleagues' work by directly modeling error in the composites, and their respective weights; this error is expected to influence estimates of MPP. By taking into account error in the composites, we can more accurately evaluate differences in MPP owing to

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[18] A 50th subsample with *n* less than 5,000 was also derived, which consisted of the *n* recruits remaining after partitioning data into the first 49 subsamples. This 50th subsample was not used in our design.
[19] This method is also known as *k*-fold (double) cross-validation.

different job family configurations and other proposed features of a classification system, so as to more confidently inform operational choices about Army classification policy. Third, the design extends Zeidner and colleagues' research by considering MPP estimates at the job family-level.

Summary of Results

As discussed earlier, the current analyses were meant to assess the impact of job family configuration and composite estimation factors on estimates of overall MPP and differences in MPP both across and within job families, taking into account composite stability. We turn to a summary of the major findings for each in turn.

Overall MPP. To evaluate the effects of job family configuration and composite estimation factors on overall MPP, we obtained estimates of overall MPP using the aforementioned procedure. These estimates were then analyzed using a standard analysis of variance (ANOVA) with MPP as the dependent variable, and the independent variables being the three factors comprising our design (with abbreviations in parentheses): (a) job family configuration (JFCONFIG); (b) no constraint vs. positive constraint (CONSTRAINT); and (c) unstandardized vs. standardized weights (STAND). Results from this ANOVA are summarized in Table 8. From the results, we observed the following.

First, neither the main effect nor interactions involving CONSTRAINT were statistically significant ($p > .05$). Similarly, associated effect sizes (R^2) were zero. Therefore, even without taking into account estimation error, constraining weights to be positive did not materially affect MPP. Second, the main effects involving STAND ($F_{(1,2450)} = 7459.934, p < .0005$) and job configuration ($F_{(2,2450)} = 1867.287, p < .0005$) were statistically significant. Because of the large sample size (N), we also computed effect size estimates. Both exhibited generally large effect sizes, with STAND (partial $R^2 = .754$, $R^2 = .517$) explaining more of the variability in MPP than JFCONFIG (partial $R^2 = .605$, $R^2 = .259$). Therefore, both standardization of weights and job configuration significantly contributed to differences in MPP. Third, and finally, there was a significant interaction between STAND and JFCONFIG ($F_{(2,2450)} = 212.346, p < .0005$), although the magnitude of this effect was noticeably smaller relative to its component main effects (partial $R^2 = .148$, $R^2 = .030$). Therefore, differences in MPP by job configuration were dependent on whether the weights were standardized or not. We investigated the nature of this effect and the above main effects more fully, including the implications of estimation error, in a series of follow-up analyses.

We followed-up the omnibus ANOVA with individual ANOVAs designed to test for simple effects, with an emphasis on job family configuration. These ANOVAs followed the omnibus model described previously, except there was a single independent variable (job family configuration) and each focused on MPP estimates obtained for a specific condition. As there were 4 conditions total (excluding job configuration), we conducted 4 ANOVAs. Results from these analyses, including estimates of standard error of MPP, are summarized in Table 9. Consistent with the significant main effect observed previously for standardization of the weights, MPP estimates tended to be systematically lower when weights were standardized. Evidence for the significant interaction between standardization and job configuration can be

Table 8
Results of Analysis of Variance (ANOVA) of Overall MPP

Factor	***F***	***df***	***Partial R^2***	***R^2***
JF Configuration (JF CONFIG)	1867.287*	2,2450	.605	.259
Constraint (CONT)	.084	1,2450	.000	.000
Standardization (STAND)	7459.934*	1,2450	.754	.517
JF CONFIG x CONT	.000	1,2450	.000	.000
JF CONFIG x STAND	212.346*	2,2450	.148	.030
JF CONFIG x CONT x STAND	.004	2,2450	.000	.000
Overall R^2	.831			

Note. * $p < .0005$. Partial R^2 represents percentage of variance in weights explained by factor, having partialed out variance attributable to the other factors. R^2 represents percentage of *total* variance in weights explained by factor.

seen in that the differences in MPP by standardization increased as the number of jobs increased. For example, looking at the 9 job family configuration, standardizing the weights produced MPP values of roughly .08 versus .12 when weights were unstandardized. When moving to the 17 job family configuration, the difference widened, as standardizing the weights produced MPP values of .09, whereas unstandardized weights resulted in MPP values around .14, roughly a 25% increase in the difference. Increasing the number of jobs almost ten-fold to 150 increased the difference, with standardized weights producing an MPP of .12 versus .19 for unstandardized weights – a 40% increase in the difference over the 17. In sum, the magnitude of the difference in overall MPP between standardized and unstandardized weights varied partly as a function of job configuration. A possible explanation, with implications for what this means operationally, are discussed shortly.

As for job family configuration, MPP significantly differed by configuration across all conditions. As evident from Table 10, differences in MPP among the three job configurations were statistically significant ($p < .0005$). The magnitude of the corresponding effect sizes (R^2) varied, ranging from low (.040) to high (.801). A closer inspection of the differences showed that overall MPP generally increased as the number of job families increased, although the rate at which MPP improved markedly declined with the added number of job families. For example, when looking at the no constraint - standardized condition, MPP goes from .083875 to .089514 (a 6.72% increase) when the number of jobs are doubled (from 9 to 17), and to .119391 (a 33.4% increase) when the number of jobs increases almost ten-fold from 17 to 150. Consistent with the significant interaction between job configuration and standardization, these differences varied by whether the weights were standardized or not. In contrast to the preceding example, for the no constraint - unstandardized condition, MPP increased from .119569 to .140396 (a 17.4% increase) when the number of jobs doubled (from 9 to 17), and to .186598 (a 32.9% increase) when increasing the number of jobs from 17 to 150. In sum, while overall MPP differed by job family configuration, such that MPP generally increased as the number of jobs increased, the rate at which MPP improved steadily declined with the added number of jobs. In addition, the magnitude of these differences and rate of improvement in MPP depended on whether weights were standardized or not.

Several important observations are of note. First, the magnitude of the standard errors of MPP observed using the current design tended to be larger than those previously reported by Zeidner and colleagues (Zeidner et al., 2000, 2003b). Although comparison values were not readily available for all conditions, the estimates produced here were generally 25% larger than those previously reported. These data suggest that test composite stability could meaningfully influence operational decisions, based on MPP, given the relatively small differences in MPP observed between many of the job family configurations and across conditions.

Second, and related to the first point, taking into account the standard error of MPP, there was sizeable overlap in MPP across the job family configurations (see Table 10). In particular, there was considerable overlap in overall MPP when weights were standardized and when comparing the 9 to the 17 job family configurations. For example, looking at the no constraint - standardized condition, there was substantial overlap in the confidence intervals for MPP for the 9, 17, and, to a lesser extent, 150 job family configurations. Practically, this confirmed that statistically significant omnibus differences in MPP by job family configuration reported previously were mainly due to differences between the 9 and 150 job families.

A third and final observation pertains to the finding that while overall MPP improved as the number of jobs increased, the magnitude of these increases diminished in relation to the number of jobs. For example, as reported above, doubling the number of jobs from 9 to 17 tended to produce a jump in overall MPP of 7% to 17%. By comparison, increasing the number of jobs ten-fold at best increased MPP by one-third (33% total). This suggests that most of the differentiation among jobs, given the population of Army jobs from which the composites and job families were constructed, is attributable to the 9 and/or 17 job family configurations. These results support earlier analyses showing greater *between*-job than *within*-job differences for the 9 and 17 job families.

In summary, when taking into account estimation error in test composites and their respective weights, there appears to be no practical difference in overall MPP between the 9 and 17 job family configurations, and to a lesser extent, the 17 and 150 configurations. This is particularly the case when test composites are based on standardized weights. Specifically, when weights are standardized to produce predicted assignment (AA) scores with equal means and variances, observed differences in MPP were generally small and within the standard error of MPP, especially when comparing the 9 to the 17 job family configurations (.083988 versus .089706). This finding is significant for two reasons. First, from a practical perspective, MPP estimates based on standardized weights more closely satisfy existing operational constraints, as they produce a more equitable distribution of recruit quality across job families. Thus, these weights mimic statistically the distributional requirements current Army classification policy considers when classifying recruits to entry-level MOS.

A second reason for the significance of this finding is that it suggests that specific abilities and aptitudes contribute less to classification efficiency relative to general mental ability (GMA), given the current population of jobs. We are able to infer this because standardizing the weights essentially equates the composites in terms of GMA, such that what remains after standardization reflects the *unique* contributions of specific abilities and aptitudes to classification independent of GMA. According to DAT, increasing the number of jobs should maximize differences among jobs in their performance requirements, thereby increasing the

classification efficiency of a multidimensional test battery and corresponding composites based on specific aptitudes. As reported previously, larger MPP values were observed when weights were unstandardized, and the increases in MPP as the number of jobs increased (from 9 to 17 to 150) were greater than with standardized weights. These increases in MPP are generally attributable to higher predictive (or criterion-related) validities, which are largely a function of GMA (Hunter, 1983; Ree & Earles, 1991; Ree, Earles, & Teachout, 1994). When these validities were effectively equated by standardizing the weights, both the magnitude of MPP and increases in MPP from moving to 9 to 17 to 150 jobs declined appreciably. Therefore, the decline in MPP improvement as the number of jobs increases, particularly when the number of jobs is increased ten-fold, indicates that a substantial portion of the pre-standardization differentiation (i.e., differential validity) among jobs is attributable to GMA, not specific abilities and aptitudes.

MPP by Job. To evaluate the effects of job family configuration and estimation method on MPP at the job-level, we computed estimates of MPP for each job using the recorded job-level assignments and predicted performance scores from the preceding simulation. As there was no evidence from the above analyses that constraining weights to be positive materially affected MPP estimates, this factor was dropped from the design. We used the 150 MOS comprising the 150 job family configuration to define the job-levels. This enabled us to investigate how the proposed test composites would function operationally, as this is the level at which actual classification decisions are made in the field, and not at an aggregate level, such as the 9 or 17 job families. Therefore, we obtained estimates of MPP for 150 jobs using the AA assignment composites based on the 9, 17, and 150 job family configurations. To assess differences in composite estimation method, one set of MPP estimates was based on unstandardized AA weights and the second set on standardized AA weights. To facilitate their interpretation and the identification of major trends, results are represented visually in Figures 1 to 6 (Appendix E).[21] Tables containing MPPs and standard errors by job family configuration and standardization can be found in Appendix F. From these figures and tables, we identified several major trends.

First, as to be expected, and consistent with previous results (Zeidner et al., 2000, 2003b), the level of MPP differed by job. However, the magnitude and pattern of these differences noticeably varied, depending on whether weights were standardized or not. Specifically, there tended to be greater between-job differences in MPP when weights were unstandardized than standardized, such that some jobs were associated with low, and in some cases, negative MPP

[20] Each box-and-whisker plot in these figures represents the distribution of MPP for a specific job over 245 cross-samples, given a particular job family configuration (9, 17, or 150). The dot inside the box represents the median of the distribution. The width of the box represents the inter-quartile range (IQR) or middle 50% of the distribution. The whiskers extend to 1.5 IQR from the median or to the most extreme MPP in the distribution, whichever is most applicable.

Table 9

Summary of Simple Effects of Job Family Configuration on Overall MPP by Condition

	Job Family Configuration							
	9		17		150			
Condition	*MPP*	*SE*	*MPP*	*SE*	*MPP*	*SE*	*F*	R^2
1. No Constraint-Unstandardized	.119569	.014048	.140396	.014049	.186598	.013936	1468.763*	.801
2. No Constraint-Standardized	.083875	.013690	.089514	.014327	.119391	.014397	446.305*	.549
3. Positive Constraint-Unstandardized	.119840	.013932	.140553	.014150	--	--	266.594*	.353
4. Positive Constraint-Standardized	.083988	.013592	.089706	.014347	--	--	20.510*	.040

Note. * $p < .0005$.

Table 10

95% Confidence Intervals Around Estimated Overall MPP by Job Family Configuration and Condition

	Job Family Configuration					
	9		17		150	
Condition	Lower	Upper	Lower	Upper	Lower	Upper
1. No Constraint-Unstandardized	.092035	.147103	.112860	.167932	.159283	.213913
2. No Constraint-Standardized	.057043	.110707	.061433	.117595	.091173	.147609
3. Positive Constraint-Unstandardized	.092533	.147147	.112819	.168287		
4. Positive Constraint-Standardized	.057348	.110628	.061586	.117826		

Note. Confidence intervals computed using conventional formula: MPP +/- (1.96*SD).

values, whereas others produced strongly positive MPP values. For example, looking at Figure 1, under the 9 job family configuration, CO jobs were consistently associated with negative MPP values, whereas EL jobs were associated with positive MPP values. Moving to the 17 job family configuration, one observes a comparable pattern, as CO2 jobs tended to produce MPP values close to or slightly greater than zero, whereas CO1 jobs continued to attract low performers, resulting in negative MPP values. At the 150 job family configuration, while there was less consistency in MPP for families as a whole (as the families have been shredded into their constituent jobs), there was even greater between-job variability in MPP, with particular jobs (i.e., 71D) clearly benefiting over others (i.e., 11B). These findings are consistent with research by Zeidner and colleagues at the job family-level (Zeidner et al., 2000, 2003b).

In contrast, when looking at MPP based on standardized weights, there was substantially less variability in MPP across jobs. That is, unlike unstandardized weights, we did not observe jobs with relatively large positive MPP achieved at the expense of other jobs, as indicated by comparatively lower and/or negative MPPs. For example, as evident from Figure 4, MPP values for CO and EL jobs were generally comparable. Of particular interest given its centrality to the Army's mission, MPP for CO jobs was higher, on average, than MPP produced when using unstandardized weights. As with the unstandardized weights, while differences in MPP across jobs increased as the number of job families increased, from the 9 to the 17 to the 150 job family configurations, the magnitude of these differences were smaller relative to the same differences observed using the unstandardized weights.

Second, comparable to results for overall MPP, differences in job-level MPP by job family configuration tended to be small when taking into account standard error. Therefore, it was difficult to conclude that one configuration produced a substantially higher level of MPP than an alternative configuration, particularly when comparing the 9 and 17 configurations. While at the aggregate level, the magnitude of the standard error for the same job across the 9, 17, and 150 job configurations tended to be equivalent, there were sizeable overlaps in job-level MPP by configuration. For example, Combat (CO) jobs, such as 11B, 11C, and 11H, displayed relatively small standard errors (on average). However, when comparing MPP for these jobs across the three job family configurations (9, 17, 150), the observed differences in MPP by configuration were practically small, when factoring in the applicable standard errors. Similarly, where there were sizeable differences in MPP, they were primarily between the 9 and 150 configurations and not the 9 and 17 job family configurations.

In summary, results at the job-level were generally consistent with those observed for overall MPP. Both the magnitude of MPP and between-job differences in MPP were, on average, contingent on job configuration and standardization of the weights. Specifically, job-level MPP tended to be higher when weights were unstandardized than standardized. In addition, between-job differences in MPP were greater between the 9 and 150 job family configurations than between the 9 and 17 configurations, particularly when taking into account the standard error of MPP.

As before, these findings suggest that standardized weights are preferable to unstandardized weights for drawing research-based conclusions about the efficacy of proposed classification system features and when making operational classification decisions. For one, standardized weights produce less variability in MPP across jobs, ensuring a more equitable distribution of recruit quality while at the same time yielding overall Army classification

benefits. Results based on standardized weights indicate that classification benefits could be achieved in a manner that is consistent with Army distributional requirements. A second advantage of standardized weights is that they produce significantly fewer jobs exhibiting negative MPP values; that is, fewer jobs where average aggregate performance is expected to be negative. In particular, for certain jobs that are especially critical to the Army's mission (i.e., CO), using standardized weights for classification resulted in higher MPP compared to the MPP obtained using unstandardized weights.

Taken together, these findings confirm that standardized weights are more likely to maximize aggregate performance, while ensuring an equitable distribution of recruit quality across jobs. By approximating Army distributional requirements, assignments based on standardized weights should theoretically require fewer ad-hoc adjustments by Army personnel managers. This is beneficial because such adjustments, which will likely be unsystematic, would otherwise negate the classification efficiency of the proposed regression-weighted test composites.

Discussion

As noted by Pearlman (1980), job classification research involves both a process and a product. The purpose of the current report was to evaluate the process and product of the proposed AA test composites and their efficacy in Army classification. In this case, *process* refers to how the AA composites were derived, whereas *product* references the stability and classification potential of the composites. This section is organized as follows. First, we summarize the major findings from our evaluation of the test composites and we review outstanding implementation issues. Second, we make recommendations regarding the adoption of the proposed AA composites. Third, and finally, we offer several suggestions for future research to further improve Army classification and selection.

Summary of Major Findings

Our evaluation focused on investigating the stability and differential validity associated with the proposed regression-weighted AA composites, and their practical effects on classification efficiency (as measured by MPP). In particular, we focus on differences between the 9 AA composites and an alternative set of 17 composites, which represent different versions of the assignment tier in the "operational" version of Zeidner and colleagues' proposed two-tiered classification system. Overall, we found the following:

First, regression-weighted test composites for the 9 and 17 job family configurations demonstrated the greatest stability. Both the composites as a whole, and their respective weights, displayed smaller standard errors and fewer problems (i.e., collinearity, "weak" data) than those for the 150 job family configuration. Based on our findings, the stability of the test composites comprising the 150 job family for use in assigning recruits to entry-level MOS configuration is questionable. This is because the lower n, on average, on which estimates are based, is associated with higher standard errors and greater susceptibility to inflation due to multicollinearity present among the ASVAB subtests. There is no compelling evidence that the 9 are necessarily more stable than the 17, as both are based on families of relatively large n and the effects of multicollinearity and "weak" data are comparable across the two sets of composites.

Second, as currently constructed, the 9 and 17 AA composites demonstrated between-family differences in validities, even when taking into account sampling error. Specifically, both the 9 and 17 AA composites displayed systematic between-family differences in: (a) composite validities (*R*s), operationalized as differences in their respective weights, both individually and as a full set; and (b) predicted performance scores (*r*). However, these differences varied by job family, such that some families (i.e., Clerical and Mechanical Maintenance) within each set of composites were more consistently and strongly differentiated from the other jobs than others. Equally as important, shredding-out families and composites at the 9 job family configuration to produce the 17 configuration resulted in mixed findings. Whereas some jobs displayed greater differentiation in validities and predicted performance scores, other jobs did not. Therefore, the gains in differential validity were not uniform. Equally as important, they were partially offset by losses in differentiation for other jobs. Overall, moving to the 17 AA composites does not appear to produce greater levels of differential validity than that observed with the 9 AA composites.

Third, and most importantly, differences in mean predicted performance (MPP) among the 9, 17, and 150 AA test composites were not practically significant, especially after taking into account estimation error in MPP. That is, both overall MPP and job-level MPP did not substantially differ across job family configuration, particularly between the 9 and 17 AA composites, after considering variability in MPP due to estimation error. The finding that there is no practical difference in MPP between the 9 and 17 AA composite is consistent with recent research (Zeidner et al., 2003b). In addition, we considered the practical effects on MPP of several operational issues related to how test composites, and their respective weights, are estimated. Whereas, constraining weights to be positive did *not* meaningfully impact MPP, standardizing predicted performance scores to have equal means and variance did. Specifically, standardized weights produced somewhat lower (on average) overall MPP than unstandardized weights, but a more equitable distribution in MPP across jobs and, in some cases, higher MPP for jobs (i.e., Combat) critical to the Army's mission. Because it already integrates important operational constraints, a classification system based on standardized weights will require fewer interventions that might otherwise negate the intended benefits of regression-weighted composites.

In considering outstanding implementation issues, the most prominent issue pertains to cut scores for the 17 and 150 AA composites. We estimated cut scores for the 17 and 150 AA composites, equating the new cut scores with cut scores for the 9 AA composites, so as to produce comparable MPP values. Cut scores and overall selection ratio by MOS based on the 17 and 150 AA composites, with accompanying documentation on our cut score equating method, are reported in Appendix G. As can be seen from these data, moving to the 17 or 150 AA composites would produce changes in cut scores. While these changes are generally small, 1-3 points, even small changes could be associated with substantial costs given the number of MOS affected. More importantly, the selection ratios (percentage of recruits qualifying for an MOS) likewise change. For example, at the 17 job family levels, the change in percentage qualifying ranges from less than 1% to 3%, whereas with the 150 job family level the percentage change ranges from less than 1% to 18%. To ensure comparable fill-rates with the new cut scores would necessitate potentially even larger changes in cut scores. Therefore, adoption of the 17 or 150 AA composites for classification would necessitate substantive changes in cut scores to achieve comparable levels of MPP or fill-rates.

Recommendations

Based on the above findings, we recommend adoption of the 9 AA composites based on standardized weights for use in assigning recruits to entry-level MOS. There are two reasons for this. First, consistent with previous research (Zeidner et al., 2003b), moving from 9 to 17 AA composites does not produce a practically significant increase in either overall MPP or MPP by MOS. This is particularly true once one takes into account estimation error in MPP. Coupled with the administrative costs and other management-related issues associated with changing existing cut scores based on the 9 composites, the technical and/or practical advantages to adopting the 17 AA test composites, as currently constructed, are few. The same holds for the 150 AA test composites, whose weights are considerably less stable and reliable than the 9 or 17 composites and, thereby, less technically defensible and feasible for supporting assignment decisions.

The second advantage to adopting the 9 AA composites based on standardized weights is that they promote a more equitable distribution of MPP across MOS than unstandardized composites. Practically, this means that lower quality recruits are less likely to be disproportionately assigned to selected MOS, specifically those with lower ASVAB predictive validities, and vice versa with higher quality recruits. Standardized composites accomplish this by statistically approximating critical operational requirements, such as MOS distributional requirements, when assigning recruits to MOS. In doing so, standardized composites retain the classification efficiency of regression-weighted composites, while taking into account practical operational concerns that might otherwise reduce their benefits. If unstandardized composites were used, Army classification managers and other decision-makers would have to make greater adjustments to assignments based on regression-weighted composites in order to achieve practical objectives (i.e., distributional requirements, fill-rates). Since these adjustments are discretionary and not likely to be implemented systematically across recruits and/or MOS, they could be expected to negate the classification potential of the 9 (standardized) composites. In sum, standardized composites will more effectively balance the optimization of aggregate Soldier performance with the need to satisfy equally important, practical requirements.

Suggestions for Future Research

There are several avenues for future research. First, future research should consider the effects of basic and technical training on Soldier proficiency and its implications for Army classification. That is, as currently computed, estimates of aggregate Soldier performance, such as MPP, do not consider training effects, although these effects are present. That is, while test composites, and their respective weights, are corrected to the Army Input population, the ASVAB-SQT validities on which they are based are conditioned on those recruits who: (a) successfully passed training (i.e., lower performers have a greater probability of attriting during technical training); and (b) experienced the performance-enhancing effects of training (i.e., as training increases recruit performance). Therefore, the contributions of basic and technical training to Soldier proficiency and its implications for classification, and measures of its effectiveness (i.e., MPP), are not readily understood. More importantly, understanding the effects of training on Soldier proficiency could prove beneficial for operational reasons. That is, when making entry-level assignments, considering the performance-enhancing effects of training is likely to open up a greater number of jobs any given recruit could be assigned to, particularly those recruits whose AA scores substantially limit the number of jobs for which he/she qualifies. If more jobs are available

to a recruit, the differentiation (differential validity) among the jobs has a greater opportunity to contribute to classification efficiency, since the ability of job-specific test composites to differentiate among the jobs is maximized. This will be especially true for recruits with lower AA scores, who traditionally have been difficult to place. In sum, methodologies that integrate the effects of training and classification into a single personnel management framework are likely to prove beneficial for both research and operational purposes.

Second, over the past decade, there has been increasing recognition that the nature of work and job performance in many jobs has changed (Howard, 1995; Ilgen & Pulakos, 1999; Schmitt & Chan, 1998). In some cases, these changes have been dramatic. The increasing use of technology, the shift to team-based or service-oriented work arrangements, and rapid environmental and organizational changes all necessitate different types of skills and aptitudes (i.e., adaptability, interpersonal skills, customer service orientation), or different levels of the same aptitudes, for successful performance than did jobs a decade ago. These changes have not only impacted jobs in the civilian sector, but military jobs as well. For example, over the past dozen years, the technological complexity of jobs, such as Combat (CO), has grown substantially with the advent of new technologies and weaponry. However, the current analyses are based on a population of jobs and predictor-criterion data that are fifteen years old. As a result, the proposed test composites, and their respective weights, are unlikely to reflect these changes. If the population of Army jobs and magnitude of predictor-criterion relations have changed, as a function of systematic changes in the content and performance requirements of these jobs, classification decisions based on the proposed composites are likely to be affected.

Third, future research is needed that constructs and evaluates the classification potential of composites that include noncognitive variables, such as personality and vocational interests. There is a growing body of research from applied psychology showing that personality and other noncognitive variables are predictive of performance across a wide range of occupations and are generally uncorrelated with and add incremental validity over and above cognitive ability, and that predictive validities differ by job content and performance requirements (Barrick & Mount, 1991; Barrick, Mount, & Judge, 2001; Hough & Furnham, 2003; McHenry, Toquam, Hanson, & Ashworth, 1990; Mount & Barrick, 1995; Mount, Barrick, & Stewart, 1998; Schmidt & Hunter, 1998). More specific to the Army, research from Project A demonstrated that predictor composites reflecting different *mixes* of cognitive aptitudes, personality traits, interests, and background characteristics more strongly differentiated and predicted performance, including technical proficiency, across jobs than predictor composites based on aptitude alone (Wise, McHenry, & Campbell, 1990). On the basis of this evidence, noncognitive variables, specifically personality and vocational interests, could greatly extend the classification potential of cognitively-based composites. We presently know of few studies (e.g., Wise et al., 1990) that consider the effectiveness of composites incorporating noncognitive variables in a multiple job context.

Conclusion

In an earlier report (Diaz et al., 2004) we independently replicated Zeidner, Johnson, and colleagues' method of empirically deriving AA composites, including the 9 AA composites currently in operational use. The primary purpose of the current report was to evaluate the efficacy of the proposed AA composites, and corresponding job families, to meet the Army's classification objectives. Presently, there has been a long-standing debate about the degree to which regression-weighted composites tailored to specific jobs based on test batteries assessing

specialized aptitudes and abilities, such as the ASVAB, produce differences in validities that represent "true" between-job differences and *not* differences due to sampling error or other artifacts (Hunter, 1983, 1985; Hunter et al., 1985; Schmidt et al., 1988; Schmidt et al., 1981; Zeidner & Johnson, 1994; Zeidner et al., 1997). To address these issues, we tested the stability and differential validity of the proposed AA composites and accompanying job families, particularly the 17 and 150 relative to the 9 AAs, and their practical effects on classification efficiency, as measured by MPP.

Overall, our findings supported the continued use of standardized AA composites when assigning recruits to entry-level MOS based on the 9 job families proposed by Zeidner and colleagues. We recommended these composites over the 17 and 150 AA composites for two reasons. First, consistent with recent research (Zeidner et al., 2003b), moving from 9 to 17 AA composites did not produce practically significant increases in either overall MPP or MPP by MOS. Second, and more importantly, the 9 AA composites based on standardized weights displayed operationally desirable properties relative to unstandardized composites. More specifically, standardized composites can be expected to more effectively balance the optimization of aggregate soldier performance with the need to satisfy quality distribution requirements. In summary, when coupled with the administrative costs and other management-related issues associated with changing existing cut scores based on the existing composites, the technical and/or practical advantages to adopting the 17 or 150 AA test composites, as currently constructed, are few.

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APPENDIX A: IDENTIFYING WEAK TEST COMPOSITES BY JOB FAMILY

Table 1
Chi-Square (χ^2) Significance Tests and Observed Significance Values (p) of Full Test Composites for 9 and 17 Job Families

Job Family Configuration					
9			17		
JF	χ^2	*p*	*JF*	χ^2	*p*
CL	11558.522	.0005	**CL1**	**6818.712**	.0005
CO	4799.789	.0005	CL2	6060.484	.0005
EL	8026.876	.0005	CO1	2005.642	.0005
FA	3900.326	.0005	CO2	4918.017	.0005
GM	7268.939	.0005	EL1	5036.132	.0005
MM	15148.526	.0005	EL2	3429.786	.0005
OF	**6980.239**	.0005	EL3	1773.143	.0005
SC	4153.739	.0005	FA	3900.326	.0005
ST	5224.271	.0005	GM1	3952.679	.0005
			GM2	3411.606	.0005
			MM1	13237.128	.0005
			MM2	2610.497	.0005
			OF	6980.239	.0005
			SC	2831.936	.0005
			ST1	2047.810	.0005
			ST2	945.654	.0005
			ST3	2857.677	.0005

Table 2
Chi-Square (χ^2) Significance Tests and Observed Significance Values (p) of Full Test Composites for 150 Job Families

JF	χ^2	*p*	*JF*	χ^2	*p*	*JF*	χ^2	*p*
11B	709.341	.0005	41C	89.921	.0005	**67U**	641.690	.0005
11C	1327.798	.0005	44B	618.032	.0005	67V	293.000	.0005
11H	1436.565	.0005	44E	406.202	.0005	67Y	314.778	.0005
11M	737.056	.0005	45B	424.318	.0005	68B	47.952	.0005
12B	1360.064	.0005	45D	104.433	.0005	68D	147.108	.0005
12C	621.414	.0005	45E	112.815	.0005	68F	229.293	.0005
12F	202.128	.0005	45K	270.569	.0005	68G	379.430	.0005
13B	1450.504	.0005	45L	110.801	.0005	68J	183.517	.0005
13C	330.875	.0005	45N	230.564	.0005	68M	85.922	.0005
13E	871.916	.0005	45T	153.416	.0005	68N	171.416	.0005
13F	1249.410	.0005	46Z	92.747	.0005	68Z	316.973	.0005
13M	160.805	.0005	51B	612.184	.0005	71D	265.462	.0005
13N	608.520	.0005	51K	206.542	.0005	71G	196.133	.0005
13R	114.789	.0005	51M	53.404	.0005	71L	891.946	.0005
14D	255.150	.0005	51R	245.330	.0005	71M	261.790	.0005
16E	213.501	.0005	51T	101.361	.0005	72E	407.533	.0005
16P	329.620	.0005	52C	133.635	.0005	72G	374.477	.0005
16R	656.949	.0005	52D	2804.757	.0005	73C	347.823	.0005
16S	873.658	.0005	54B	1151.399	.0005	73D	124.266	.0005
19D	1731.238	.0005	55B	732.155	.0005	74B	297.171	.0005
19E	1598.995	.0005	55D	104.757	.0005	75B	1027.360	.0005
19K	2109.316	.0005	57E	48.911	.0005	75C	440.022	.0005
24Z	94.226	.0005	62B	2584.832	.0005	75D	382.113	.0005
25S	185.047	.0005	62E	613.813	.0005	75E	297.767	.0005
27E	149.253	.0005	62F	279.622	.0005	75F	84.000	.0005
29V	280.653	.0005	62J	301.906	.0005	76J	145.302	.0005
31C	1298.584	.0005	63B	4663.062	.0005	76P	754.372	.0005
31K	1817.933	.0005	63D	483.193	.0005	76V	1469.456	.0005
31L	1010.712	.0005	63E	784.828	.0005	76X	232.600	.0005
31N	171.582	.0005	63G	192.546	.0005	77F	2262.809	.0005
31P	65.980	.0005	63H	787.042	.0005	77W	188.913	.0005
31Q	448.591	.0005	63J	439.219	.0005	81L	51.228	.0005
31R	1641.633	.0005	63N	397.469	.0005	82C	435.702	.0005
31S	53.965	.0005	63S	853.245	.0005	88H	218.646	.0005
31V	1158.409	.0005	63T	851.795	.0005	88M	1857.942	.0005
35E	306.780	.0005	63W	2809.063	.0005	88N	106.659	.0005
35H	25.948	.0005	63Y	495.336	.0005	91A	965.583	.0005
35J	212.899	.0005	67N	490.582	.0005	91D	187.595	.0005
35N	195.246	.0005	67R	88.011	.0005	91E	129.463	.0005
36M	265.538	.0005	67T	519.506	.0005	91F	20.898	.0039

Table 2 (cont'd)

JF	χ^2	*p*
91G	76.993	.0005
91K	107.459	.0005
91M	98.880	.0005
91P	153.012	.0005
91Q	218.886	.0005
91R	177.217	.0005
91S	172.979	.0005
91T	50.632	.0005
91Z	89.284	.0005
92A	1194.597	.0005
92G	2333.944	.0005
92M	78.059	.0005
92R	137.606	.0005
92Y	521.576	.0005
93C	100.394	.0005
93P	784.817	.0005
95B	952.766	.0005
95C	50.307	.0005
96B	345.164	.0005
96D	258.185	.0005
96R	335.927	.0005
97B	90.395	.0005
98C	110.505	.0005
98G	87.785	.0005
98H	217.285	.0005
98Z	169.611	.0005
55G + 93F	123.553	.0005
27Z + 29Z	265.223	.0005
25M + 25Z + 97E	91.532	.0005
15E + 16J	63.173	.0005

Table 3

T-Tests and Observed Significance Values (p) of Test Composite Weights by ASVAB Subtest for 9 Job Families

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
CL	***0.000***	***0.0071***	*1.0000*	-37.961	**0.0066**	**0.0005**	-4.818	0.0055	**0.0005**	**-27.412**	0.0069	**0.0005**
CO	-4.218	0.0119	0.0005	-8.138	0.0105	0.0005	-13.600	0.0090	0.0005	-15.425	0.0109	0.0005
EL	-2.473	0.0094	0.0134	-17.154	0.0085	0.0005	-19.386	0.0069	0.0005	-17.827	0.0085	0.0005
FA	-2.785	0.0153	0.0053	-8.934	0.0136	0.0005	-9.720	0.0116	0.0005	-11.461	0.0145	0.0005
GM	-6.984	0.0097	0.0005	-18.023	0.0084	0.0005	-24.670	0.0077	0.0005	-15.791	0.0092	0.0005
MM	-2.537	0.0079	0.0112	-17.175	0.0069	0.0005	-52.373	0.0064	0.0005	-12.667	0.0075	0.0005
OF	-3.701	0.0108	0.0005	-17.799	0.0094	0.0005	-20.457	0.0085	0.0005	-9.778	0.0104	0.0005
SC	***0.000***	***0.0124***	***1.0000***	-12.647	0.0109	0.0005	-9.231	0.0093	0.0005	-17.260	0.0112	0.0005
ST	-3.001	0.0110	0.0027	-17.026	0.0098	0.0005	-10.959	0.0076	0.0005	-14.695	0.0101	0.0005

Note. Effect sizes that are *not* statistically significant (p > .05) are bold and italicized.

Table 3 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
CL	-6.381	0.0057	**0.0005**	-4.914	0.0063	**0.0005**	-32.112	0.0065	**0.0005**	49018
CO	-10.092	0.0099	0.0005	-5.784	0.0105	0.0005	-6.576	0.0112	0.0005	41910
EL	-11.326	0.0074	0.0005	-13.352	0.0082	0.0005	-19.229	0.0081	0.0005	27776
FA	-9.072	0.0130	0.0005	-3.530	0.0139	0.0005	-6.999	0.0144	0.0005	11740
GM	-12.101	0.0078	0.0005	-12.415	0.0087	0.0005	-7.718	0.0088	0.0005	23572
MM	-19.342	0.0068	0.0005	-15.658	0.0072	0.0005	-10.724	0.0074	0.0005	37645
OF	-11.854	0.0092	0.0005	-6.989	0.0098	0.0005	-11.032	0.0103	0.0005	21300
SC	-7.679	0.0100	0.0005	-10.486	0.0107	0.0005	-13.846	0.0115	0.0005	13981
ST	-10.981	0.0086	0.0005	-6.325	0.0089	0.0005	-18.466	0.0110	0.0005	30868

Note. Effect sizes that are *not* statistically significant (p > .05) are bold and italicized.

Table 4

T-Tests and Observed Significance Values (p) of Test Composite Weights by ASVAB Subtest for 17 Job Families

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
CL1	***0.000***	***0.0092***	***1.0000***	-30.305	0.0085	**0.0005**	0.000	0.0074	**0.0005**	-25.641	0.0089	**0.0005**
CL2	***0.000***	***0.0100***	***1.0000***	-25.356	0.0093	0.0005	-8.037	0.0076	0.0005	-17.267	0.0097	0.0005
CO1	-2.688	0.0168	0.0072	-4.543	0.0148	**0.0005**	-9.142	0.0127	**0.0005**	-11.735	0.0154	**0.0005**
CO2	-4.155	0.0142	0.0005	-9.382	0.0125	0.0005	-12.448	0.0107	0.0005	-11.189	0.0131	0.0005
EL1	***-0.683***	***0.0126***	***0.4948***	-12.715	0.0111	**0.0005**	-17.925	0.0092	**0.0005**	-11.526	0.0113	**0.0005**
EL2	-2.936	0.0143	0.0033	-9.597	0.0130	0.0005	-12.581	0.0103	0.0005	-14.308	0.0131	0.0005
EL3	***-1.032***	***0.0194***	***0.3021***	-11.127	0.0177	**0.0005**	-4.595	0.0144	**0.0005**	-7.629	0.0175	**0.0005**
FA	-2.785	0.0153	0.0053	-8.934	0.0136	0.0005	-9.720	0.0116	0.0005	-11.461	0.0145	0.0005
GM1	-4.406	0.0140	0.0005	-17.144	0.0120	**0.0005**	-18.014	0.0111	**0.0005**	-9.250	0.0133	**0.0005**
GM2	-5.434	0.0135	0.0005	-8.848	0.0118	0.0005	-16.968	0.0107	0.0005	-12.930	0.0129	0.0005
MM1	-2.795	0.0088	0.0052	-13.940	0.0077	**0.0005**	-51.871	0.0071	**0.0005**	-10.178	0.0084	**0.0005**
MM2	***-0.041***	***0.0181***	***0.9675***	-10.840	0.0150	0.0005	-13.146	0.0149	0.0005	-8.234	0.0163	0.0005
OF	-3.701	0.0108	0.0005	-17.799	0.0094	**0.0005**	-20.457	0.0085	**0.0005**	-9.778	0.0104	**0.0005**
SC	***0.000***	***0.0156***	***1.0000***	-9.904	0.0139	0.0005	-7.143	0.0120	0.0005	-13.516	0.0143	0.0005
ST1	-3.219	0.0174	0.0013	-10.378	0.0142	**0.0005**	-6.294	0.0125	**0.0005**	-7.609	0.0153	**0.0005**
ST2	***-0.913***	***0.0252***	***0.3610***	-8.315	0.0244	0.0005	-3.566	0.0161	0.0005	-6.800	0.0241	0.0005
ST3	***-1.151***	***0.0163***	***0.2496***	-11.429	0.0138	0.0005	-9.019	0.0119	0.0005	-11.366	0.0148	0.0005

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 4 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
CL1	***0.000***	***0.0074***	***1.0000***	***0.000***	***0.0082***	***1.0000***	-31.178	0.0087	**0.0005**	27480
CL2	-8.094	0.0081	0.0005	-5.155	0.0089	0.0005	-18.186	0.0091	0.0005	21538
CO1	-6.850	0.0140	0.0005	-3.303	0.0149	0.0010	-3.543	0.0158	**0.0005**	19593
CO2	-9.172	0.0116	0.0005	-6.528	0.0125	0.0005	-7.849	0.0133	0.0005	22317
EL1	-8.403	0.0100	0.0005	-11.060	0.0110	0.0005	-13.568	0.0111	**0.0005**	13919
EL2	-8.306	0.0110	0.0005	-8.849	0.0124	0.0005	-9.562	0.0124	0.0005	10675
EL3	-4.275	0.0155	0.0005	-4.696	0.0170	0.0005	-14.707	0.0166	**0.0005**	8182
FA	-9.072	0.0130	0.0005	-3.530	0.0139	0.0005	-6.999	0.0144	0.0005	11740
GM1	-8.133	0.0112	0.0005	-11.376	0.0125	0.0005	-6.916	0.0123	**0.0005**	10440
GM2	-8.961	0.0108	0.0005	-6.423	0.0120	0.0005	-4.239	0.0126	0.0005	13132
MM1	-17.437	0.0075	0.0005	-15.296	0.0082	0.0005	-6.643	0.0083	**0.0005**	26939
MM2	-8.371	0.0155	0.0005	-4.162	0.0157	0.0005	-11.193	0.0164	0.0005	10706
OF	-11.854	0.0092	0.0005	-6.989	0.0098	0.0005	-11.032	0.0103	**0.0005**	21300
SC	-5.980	0.0129	0.0005	-8.306	0.0134	0.0005	-10.646	0.0149	0.0005	8981
ST1	-7.538	0.0138	0.0005	-3.857	0.0148	0.0005	-9.179	0.0160	**0.0005**	12653
ST2	-3.576	0.0183	0.0005	***-1.953***	***0.0188***	***0.0508***	-10.047	0.0273	0.0005	8751
ST3	-7.859	0.0134	0.0005	-5.107	0.0136	0.0005	-13.031	0.0158	0.0005	9464

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5

T-Tests and Observed Significance Values (p) of Test Composite Weights by ASVAB Subtest for 150 Job Families

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
11B	***-1.389***	***0.0227***	*0.1648*	***-1.764***	***0.0194***	***0.0778***	-5.526	0.0169	0.0005	-7.747	0.0199	0.0005
11C	***-1.730***	***0.0216***	***0.0836***	-6.984	0.0191	0.0005	-10.536	0.0165	0.0005	-6.242	0.0190	0.0005
11H	-2.985	0.0222	0.0028	-4.156	0.0194	0.0005	-10.198	0.0164	0.0005	-9.077	0.0197	0.0005
11M	-2.765	0.0237	0.0057	-4.239	0.0200	0.0005	-6.299	0.0174	0.0005	-4.697	0.0204	0.0005
12B	-3.620	0.0218	0.0005	-4.191	0.0185	0.0005	-6.553	0.0162	0.0005	-8.191	0.0193	0.0005
12C	-2.005	0.0352	0.0449	-2.626	0.0300	0.0086	-6.168	0.0259	0.0005	-5.397	0.0297	0.0005
12F	***1.355***	***0.0632***	***0.1753***	-2.058	0.0506	0.0396	-7.884	0.0457	0.0005	-2.422	0.0567	0.0154
13B	***-1.671***	***0.0215***	***0.0947***	-3.427	0.0185	0.0006	-7.129	0.0161	0.0005	-6.551	0.0196	0.0005
13C	***-0.640***	***0.0536***	***0.5224***	***0.360***	***0.0426***	***0.7187***	-6.647	0.0372	0.0005	-5.107	0.0490	0.0005
13E	***0.325***	***0.0330***	***0.7449***	-8.452	0.0299	0.0005	***-1.639***	***0.0233***	***0.1012***	-7.536	0.0284	0.0005
13F	-2.492	0.0236	0.0127	-7.452	0.0209	0.0005	-6.884	0.0171	0.0005	-7.949	0.0204	0.0005
13M	***-0.183***	***0.0547***	***0.8551***	-4.056	0.0456	0.0005	-1.994	0.0419	0.0461	-3.334	0.0455	0.0009
13N	***0.143***	***0.0282***	***0.8860***	-3.932	0.0236	0.0005	-5.751	0.0228	0.0005	-7.532	0.0268	0.0005
13R	***-0.602***	***0.0584***	***0.5474***	-3.311	0.0501	0.0009	-3.575	0.0471	0.0005	***-1.337***	***0.0551***	***0.1813***
14D	***-1.632***	***0.0549***	***0.1026***	-6.110	0.0472	0.0005	-7.184	0.0443	0.0005	***-0.058***	***0.0499***	***0.9534***
16E	-2.181	0.0540	0.0292	-3.659	0.0464	0.0005	-2.785	0.0469	0.0054	-2.628	0.0506	0.0086
16P	***-1.265***	***0.0455***	***0.2057***	-2.276	0.0347	0.0228	-6.485	0.0349	0.0005	-3.270	0.0369	0.0011
16R	***-0.956***	***0.0326***	***0.3393***	-6.550	0.0273	0.0005	-7.557	0.0255	0.0005	-3.786	0.0297	0.0005
16S	***-0.832***	***0.0303***	***0.4052***	-5.164	0.0275	0.0005	-3.998	0.0243	0.0005	-4.502	0.0286	0.0005
19D	***-1.553***	***0.0223***	***0.1205***	-5.477	0.0191	0.0005	-8.408	0.0165	0.0005	-5.542	0.0196	0.0005
19E	-3.568	0.0228	0.0005	-4.811	0.0185	0.0005	-8.460	0.0163	0.0005	-5.566	0.0188	0.0005
19K	-2.369	0.0213	0.0178	-8.803	0.0184	0.0005	-10.309	0.0153	0.0005	-3.966	0.0187	0.0005
24Z	***0.284***	***0.0600***	***0.7767***	-3.057	0.0561	0.0022	-2.647	0.0461	0.0081	***-0.313***	***0.0520***	***0.7543***
25S	***-0.974***	***0.0675***	***0.3300***	***0.655***	***0.0626***	***0.5122***	-2.219	0.0675	0.0265	-4.440	0.0627	0.0005
27E	***0.726***	***0.0510***	***0.4676***	-4.786	0.0434	0.0005	***0.537***	***0.0365***	***0.5914***	***-0.479***	***0.0435***	***0.6320***

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
29V	***-0.218***	***0.0534***	***0.8277***	-2.762	0.0532	0.0058	-3.005	0.0384	0.0027	***-1.275***	***0.0485***	***0.2021***
31C	***-0.078***	***0.0216***	***0.9379***	-6.378	0.0183	0.0005	-8.188	0.0159	0.0005	-8.450	0.0183	0.0005
31K	-2.366	0.0207	0.0180	-4.507	0.0179	0.0005	-8.290	0.0151	0.0005	-9.104	0.0181	0.0005
31L	***0.787***	***0.0277***	***0.4311***	-3.550	0.0247	0.0005	-10.244	0.0211	0.0005	-4.095	0.0248	0.0005
31N	***-1.009***	***0.0519***	***0.3130***	-3.747	0.0528	0.0005	-2.295	0.0356	0.0217	-4.447	0.0501	0.0005
31P	***1.470***	***0.0668***	***0.1415***	***-0.788***	***0.0591***	***0.4307***	-2.080	0.0493	0.0375	-3.161	0.0571	0.0016
31Q	***1.083***	***0.0409***	***0.2789***	-2.966	0.0353	0.0030	-4.742	0.0290	0.0005	-4.456	0.0358	0.0005
31R	***-1.939***	***0.0210***	***0.0525***	-8.294	0.0175	0.0005	-9.358	0.0147	0.0005	-6.279	0.0176	0.0005
31S	***-1.189***	***0.0914***	***0.2342***	-2.474	0.0880	0.0133	***-1.232***	***0.0445***	***0.2180***	-2.586	0.0750	0.0097
31V	***0.944***	***0.0236***	***0.3454***	-5.055	0.0201	0.0005	-11.174	0.0166	0.0005	-7.730	0.0198	0.0005
35E	***-1.113***	***0.0470***	***0.2657***	-6.164	0.0439	0.0005	-4.031	0.0357	0.0005	-3.569	0.0417	0.0005
35H	***-1.392***	***0.1305***	***0.1640***	***-1.688***	***0.1127***	***0.0914***	***-0.231***	***0.0616***	***0.8175***	-2.561	0.0903	0.0104
35J	***-1.762***	***0.0461***	***0.0781***	-3.271	0.0416	0.0011	***-1.815***	***0.0331***	***0.0695***	-5.471	0.0375	0.0005
35N	***1.249***	***0.0509***	***0.2115***	-2.653	0.0480	0.0080	-2.164	0.0400	0.0305	***-1.711***	***0.0528***	***0.0871***
36M	-2.551	0.0440	0.0107	***-0.441***	***0.0388***	***0.6593***	-6.407	0.0297	0.0005	-3.563	0.0371	0.0005
41C	***-0.087***	***0.0835***	***0.9303***	***-1.082***	***0.0682***	***0.2793***	-4.047	0.0604	0.0005	***-1.471***	***0.0738***	***0.1414***
44B	-2.723	0.0397	0.0065	***-1.122***	***0.0353***	***0.2620***	-10.263	0.0325	0.0005	-3.969	0.0378	0.0005
44E	-2.735	0.0528	0.0062	-2.592	0.0459	0.0095	-2.991	0.0453	0.0028	-6.106	0.0428	0.0005
45B	***0.476***	***0.0523***	***0.6339***	***-0.705***	***0.0467***	***0.4807***	-7.714	0.0467	0.0005	-2.348	0.0509	0.0189
45D	***-1.783***	***0.0684***	***0.0746***	-2.676	0.0524	0.0075	-3.248	0.0536	0.0012	***-1.135***	***0.0583***	***0.2564***
45E	***-1.546***	***0.0723***	***0.1221***	***-0.900***	***0.0565***	***0.3681***	-3.090	0.0507	0.0020	-2.099	0.0601	0.0358
45K	***1.477***	***0.0530***	***0.1397***	-5.897	0.0421	0.0005	-5.227	0.0395	0.0005	-2.683	0.0446	0.0073
45L	***-1.643***	***0.0720***	***0.1005***	***-0.112***	***0.0579***	***0.9109***	-2.346	0.0585	0.0190	-2.908	0.0594	0.0036
45N	***1.364***	***0.0570***	***0.1726***	***0.157***	***0.0498***	***0.8753***	-5.353	0.0467	0.0005	-4.304	0.0544	0.0005
45T	***-1.828***	***0.0604***	***0.0676***	-5.711	0.0541	0.0005	-4.582	0.0470	0.0005	2.060	0.0625	0.0394

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
46Z	-2.362	0.0742	0.0182	***-1.063***	***0.0598***	***0.2879***	***0.394***	***0.0484***	***0.6937***	-4.162	0.0593	0.0005
51B	***-0.672***	***0.0330***	***0.5015***	-2.316	0.0285	0.0206	-9.406	0.0241	0.0005	-5.451	0.0301	0.0005
51K	-2.875	0.0590	0.0040	***-0.674***	***0.0514***	***0.5002***	-4.002	0.0466	0.0005	-2.228	0.0586	0.0259
51M	***1.682***	***0.0860***	***0.0926***	***-0.892***	***0.0712***	***0.3721***	-2.311	0.0752	0.0209	***-0.736***	***0.0819***	***0.4618***
51R	***1.496***	***0.0551***	***0.1345***	***-1.704***	***0.0450***	***0.0884***	-5.383	0.0397	0.0005	-5.908	0.0464	0.0005
51T	***0.401***	***0.0922***	***0.6884***	***0.976***	***0.0731***	***0.3289***	-4.796	0.0620	0.0005	-4.258	0.0757	0.0005
52C	***-0.408***	***0.0638***	***0.6834***	-3.452	0.0513	0.0006	***-1.674***	***0.0489***	***0.0940***	***-1.003***	***0.0558***	***0.3161***
52D	-2.945	0.0180	0.0032	-13.854	0.0151	0.0005	-16.162	0.0138	0.0005	-10.503	0.0158	0.0005
54B	***-0.719***	***0.0378***	***0.4723***	-5.907	0.0312	0.0005	-9.035	0.0265	0.0005	-5.163	0.0320	0.0005
55B	-3.023	0.0293	0.0025	-6.656	0.0237	0.0005	-5.454	0.0222	0.0005	-4.999	0.0268	0.0005
55D	-1.974	0.0832	0.0484	-2.054	0.0622	0.0400	-3.781	0.0594	0.0005	***-0.173***	***0.0613***	***0.8630***
57E	***-1.042***	***0.0543***	***0.2973***	***0.696***	***0.0466***	***0.4864***	-3.283	0.0450	0.0010	***-1.059***	***0.0584***	***0.2897***
62B	***-1.727***	***0.0230***	***0.0842***	-4.955	0.0207	0.0005	-19.059	0.0181	0.0005	-6.337	0.0209	0.0005
62E	-2.776	0.0374	0.0055	-4.114	0.0326	0.0005	-7.863	0.0309	0.0005	-3.191	0.0323	0.0014
62F	-2.153	0.0645	0.0313	***-1.289***	***0.0507***	***0.1974***	-2.929	0.0467	0.0034	-2.309	0.0537	0.0209
62J	***-1.845***	***0.0457***	***0.0650***	***-0.974***	***0.0415***	***0.3298***	-5.894	0.0383	0.0005	-3.182	0.0449	0.0015
63B	-2.942	0.0186	0.0033	-5.562	0.0157	0.0005	-30.234	0.0138	0.0005	-4.368	0.0167	0.0005
63D	***0.748***	***0.0376***	***0.4545***	-2.012	0.0324	0.0442	-13.261	0.0341	0.0005	***-1.441***	***0.0346***	***0.1496***
63E	***-0.085***	***0.0361***	***0.9325***	***-0.618***	***0.0305***	***0.5364***	-14.304	0.0300	0.0005	-4.469	0.0330	0.0005
63G	***-0.651***	***0.0507***	***0.5150***	-3.172	0.0455	0.0015	-8.238	0.0395	0.0005	***-0.287***	***0.0461***	***0.7742***
63H	***0.670***	***0.0300***	***0.5032***	-4.913	0.0261	0.0005	-7.376	0.0223	0.0005	-3.414	0.0275	0.0006
63J	***0.921***	***0.0410***	***0.3572***	-3.464	0.0365	0.0005	-9.376	0.0306	0.0005	***-1.944***	***0.0390***	***0.0519***
63N	***-1.631***	***0.0465***	***0.1029***	***-1.612***	***0.0398***	***0.1069***	-10.485	0.0410	0.0005	-1.976	0.0429	0.0481
63S	***0.825***	***0.0264***	***0.4092***	-2.575	0.0226	0.0100	-17.087	0.0257	0.0005	-3.469	0.0243	0.0005
63T	***-0.679***	***0.0241***	***0.4969***	-4.345	0.0208	0.0005	-17.842	0.0224	0.0005	***-1.778***	***0.0213***	***0.0754***

Note. Effect sizes that are *not* statistically significant (p > .05) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
63W	***-0.809***	***0.0228***	***0.4183***	**-5.704**	**0.0209**	0.0005	-19.518	0.0181	0.0005	-2.193	0.0227	0.0283
63Y	***0.353***	***0.0428***	***0.7241***	-3.645	0.0362	0.0005	-12.236	0.0364	0.0005	***-1.779***	***0.0380***	***0.0753***
67N	***0.786***	***0.0410***	***0.4318***	-3.221	0.0334	0.0013	-9.844	0.0317	0.0005	-5.459	0.0336	0.0005
67R	***0.495***	***0.0958***	***0.6207***	-2.830	0.0763	0.0047	***-1.899***	***0.0808***	***0.0575***	***-0.427***	***0.0873***	***0.6693***
67T	***0.438***	***0.0379***	***0.6612***	-3.089	0.0318	0.0020	-7.925	0.0299	0.0005	-5.593	0.0313	0.0005
67U	-2.023	0.0362	0.0431	-6.223	0.0275	0.0005	-7.864	0.0271	0.0005	-4.710	0.0296	0.0005
67V	***0.329***	***0.0397***	***0.7420***	-3.307	0.0329	0.0009	-5.262	0.0314	0.0005	-1.972	0.0318	0.0487
67Y	***0.081***	***0.0450***	***0.9355***	-3.400	0.0366	0.0007	-6.569	0.0365	0.0005	***-1.627***	***0.0351***	***0.1037***
68B	***-0.003***	***0.0682***	***0.9974***	***0.915***	***0.0591***	***0.3602***	***-1.056***	***0.0529***	***0.2909***	-3.365	0.0568	0.0008
68D	***0.436***	***0.0572***	***0.6630***	***-1.357***	***0.0491***	***0.1747***	-4.060	0.0494	0.0005	-3.972	0.0481	0.0005
68F	***-1.500***	***0.0551***	***0.1335***	-4.286	0.0469	0.0005	-3.265	0.0453	0.0011	-2.849	0.0466	0.0044
68G	***-1.890***	***0.0499***	***0.0588***	-6.762	0.0416	0.0005	***-1.628***	***0.0403***	***0.1035***	-3.246	0.0403	0.0012
68J	***-1.079***	***0.0484***	***0.2804***	-2.729	0.0409	0.0063	-2.764	0.0334	0.0057	-4.201	0.0376	0.0005
68M	***-1.607***	***0.0752***	***0.1080***	***1.404***	***0.0688***	***0.1602***	-3.340	0.0579	0.0008	***-1.537***	***0.0677***	***0.1244***
68N	***0.257***	***0.0721***	***0.7970***	***-1.844***	***0.0580***	***0.0652***	***-0.995***	***0.0500***	***0.3200***	-4.118	0.0585	0.0005
68Z	***0.586***	***0.0508***	***0.5580***	-7.210	0.0475	0.0005	***-1.087***	***0.0364***	***0.2770***	-4.297	0.0454	0.0005
71D	***1.523***	***0.0387***	***0.1277***	-6.100	0.0381	0.0005	***0.873***	***0.0273***	***0.3829***	-7.152	0.0363	0.0005
71G	***-1.862***	***0.0421***	***0.0626***	-5.760	0.0366	0.0005	***1.894***	***0.0331***	***0.0582***	-3.707	0.0392	0.0005
71L	***1.657***	***0.0203***	***0.0975***	-13.548	0.0179	0.0005	3.737	0.0165	0.0005	-10.649	0.0183	0.0005
71M	***-0.257***	***0.0498***	***0.7969***	-3.233	0.0419	0.0012	***-1.604***	***0.0352***	***0.1088***	-3.499	0.0418	0.0005
72E	***0.650***	***0.0368***	***0.5158***	-2.078	0.0329	0.0377	-2.837	0.0281	0.0045	-6.558	0.0331	0.0005
72G	***-0.172***	***0.0362***	***0.8637***	-4.581	0.0316	0.0005	***1.654***	***0.0284***	***0.0982***	-6.045	0.0323	0.0005
73C	***1.777***	***0.0303***	***0.0755***	-7.951	0.0279	0.0005	***0.814***	***0.0259***	***0.4155***	-7.240	0.0289	0.0005
73D	***-0.927***	***0.0688***	***0.3542***	-2.430	0.0601	0.0151	***0.793***	***0.0508***	***0.4279***	-5.252	0.0626	0.0005
74B	***0.238***	***0.0432***	***0.8117***	-5.198	0.0383	0.0005	2.154	0.0315	0.0312	-3.488	0.0412	0.0005

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
75B	2.523	0.0211	0.0116	-12.848	0.0201	0.0005	***-0.758***	***0.0164***	***0.4482***	-12.820	0.0201	0.0005
75C	*-0.316*	***0.0270***	***0.7518***	-9.993	0.0245	0.0005	***0.709***	***0.0225***	***0.4784***	-7.303	0.0272	0.0005
75D	***1.254***	***0.0275***	***0.2097***	-9.131	0.0259	0.0005	***0.180***	***0.0224***	***0.8571***	-9.106	0.0254	0.0005
75E	2.104	0.0359	0.0354	-8.970	0.0326	0.0005	***0.908***	***0.0283***	***0.3638***	-6.361	0.0340	0.0005
75F	***-0.038***	***0.0608***	***0.9695***	-5.027	0.0552	0.0005	-2.249	0.0425	0.0245	-3.124	0.0573	0.0018
76J	***1.055***	***0.0420***	***0.2913***	-5.221	0.0400	0.0005	***-0.687***	***0.0341***	***0.4923***	-5.943	0.0428	0.0005
76P	***0.834***	***0.0259***	***0.4041***	-9.585	0.0235	0.0005	3.231	0.0211	0.0012	-9.249	0.0239	0.0005
76V	***-0.812***	***0.0203***	***0.4169***	-8.431	0.0185	0.0005	-4.196	0.0158	0.0005	-4.833	0.0192	0.0005
76X	***1.033***	***0.0571***	***0.3015***	-5.358	0.0487	0.0005	***0.023***	***0.0495***	***0.9814***	***-1.461***	***0.0553***	***0.1441***
77F	-2.848	0.0198	0.0044	-8.451	0.0180	0.0005	-13.304	0.0145	0.0005	-7.598	0.0182	0.0005
77W	***0.471***	***0.0536***	***0.6380***	-2.474	0.0432	0.0133	-2.408	0.0397	0.0160	-2.925	0.0496	0.0034
81L	***0.127***	***0.0845***	***0.8992***	-2.730	0.0695	0.0063	-2.227	0.0696	0.0260	***-0.997***	***0.0753***	***0.3185***
82C	***-1.907***	***0.0464***	***0.0565***	-3.973	0.0411	0.0005	-4.840	0.0336	0.0005	-7.020	0.0417	0.0005
88H	***0.183***	***0.0386***	***0.8544***	***-1.156***	***0.0338***	***0.2479***	-6.668	0.0291	0.0005	-6.335	0.0353	0.0005
88M	***-0.956***	***0.0207***	***0.3389***	-6.624	0.0180	0.0005	-14.504	0.0158	0.0005	-2.270	0.0195	0.0232
88N	***1.495***	***0.0358***	***0.1349***	-4.548	0.0309	0.0005	***-0.252***	***0.0264***	***0.8010***	-3.095	0.0322	0.0020
91A	***-1.949***	***0.0226***	***0.0513***	-5.676	0.0180	0.0005	-6.937	0.0160	0.0005	-5.050	0.0190	0.0005
91D	-4.535	0.0561	0.0005	-3.880	0.0437	0.0005	***0.919***	***0.0403***	***0.3582***	-3.403	0.0486	0.0007
91E	***-0.623***	***0.0459***	***0.5333***	-6.000	0.0354	0.0005	3.544	0.0332	0.0005	***-0.971***	***0.0387***	***0.3313***
91F	***1.810***	***0.0829***	***0.0702***	***-1.641***	***0.0589***	***0.1009***	***-1.921***	***0.0537***	***0.0547***	-2.081	0.0727	0.0374
91G	-2.331	0.0891	0.0198	-2.667	0.0766	0.0077	***-0.070***	***0.0614***	***0.9438***	***-0.697***	***0.0773***	***0.4856***
91K	***1.461***	***0.0457***	***0.1439***	-2.286	0.0387	0.0222	2.409	0.0319	0.0160	-5.305	0.0427	0.0005
91M	***-0.468***	***0.0658***	***0.6396***	-2.785	0.0511	0.0054	***0.488***	***0.0521***	***0.6252***	***-1.019***	***0.0613***	***0.3081***
91P	***-1.465***	***0.0618***	***0.1428***	-4.336	0.0504	0.0005	***-0.988***	***0.0418***	***0.3232***	-4.887	0.0518	0.0005
91Q	-2.496	0.0624	0.0126	-3.675	0.0552	0.0005	***-0.179***	***0.0402***	***0.8577***	-2.072	0.0544	0.0382

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest											
	GS			AR			AS			MK		
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*
91R	-2.106	0.0618	0.0352	-5.505	0.0504	0.0005	***0.345***	***0.0460***	***0.7300***	-2.266	**0.0523**	0.0235
91S	***-0.643***	***0.0706***	***0.5202***	-2.461	0.0587	0.0139	***-0.253***	***0.0498***	***0.8003***	***-1.344***	***0.0624***	***0.1790***
91T	***0.118***	***0.0888***	***0.9065***	-2.269	0.0744	0.0232	***-0.883***	***0.0572***	***0.3773***	-2.787	0.0680	0.0053
91Z	***-0.412***	***0.0637***	***0.6802***	-2.978	0.0486	0.0029	***0.908***	***0.0468***	***0.3640***	***-0.352***	***0.0534***	***0.7251***
92A	***1.810***	***0.0206***	***0.0703***	-13.158	0.0186	0.0005	-2.119	0.0150	0.0341	-10.676	0.0186	0.0005
92G	-3.194	0.0197	0.0014	-10.087	0.0169	0.0005	-10.838	0.0153	0.0005	-3.269	0.0191	0.0011
92M	-2.338	0.0874	0.0194	-4.041	0.0728	0.0005	***-1.387***	***0.0696***	***0.1655***	***1.073***	***0.0748***	***0.2835***
92R	***0.186***	***0.0511***	***0.8527***	***-0.705***	***0.0425***	***0.4807***	-3.791	0.0383	0.0005	-5.167	0.0451	0.0005
92Y	***1.101***	***0.0206***	***0.2707***	-9.231	0.0192	0.0005	***-1.486***	***0.0161***	***0.1372***	-7.485	0.0196	0.0005
93C	***0.345***	***0.0636***	***0.7303***	***-1.062***	***0.0604***	***0.2881***	***-0.494***	***0.0493***	***0.6214***	-2.500	0.0602	0.0124
93P	***0.669***	***0.0365***	***0.5033***	-9.310	0.0279	0.0005	***0.046***	***0.0255***	***0.9634***	-5.694	0.0310	0.0005
95B	***-0.527***	***0.0224***	***0.5983***	-6.209	0.0184	0.0005	-5.419	0.0161	0.0005	-7.249	0.0193	0.0005
95C	***0.196***	***0.0802***	***0.8448***	-3.456	0.0651	0.0005	***-1.087***	***0.0573***	***0.2772***	***-1.060***	***0.0846***	***0.2891***
96B	***0.340***	***0.0512***	***0.7338***	-4.896	0.0407	0.0005	-2.725	0.0326	0.0064	-6.413	0.0401	0.0005
96D	***-0.352***	***0.0730***	***0.7245***	-2.703	0.0626	0.0069	-3.738	0.0531	0.0005	-4.772	0.0563	0.0005
96R	***0.437***	***0.0490***	***0.6620***	-2.776	0.0421	0.0055	-7.596	0.0387	0.0005	-2.612	0.0436	0.0090
97B	***-1.566***	***0.0883***	***0.1174***	***-0.054***	***0.0689***	***0.9569***	***0.342***	***0.0537***	***0.7325***	-2.656	0.0671	0.0079
98C	***0.681***	***0.0719***	***0.4956***	-3.621	0.0747	0.0005	***-1.327***	***0.0446***	***0.1846***	-2.422	0.0663	0.0154
98G	***-0.074***	***0.0604***	***0.9406***	-3.136	0.0558	0.0017	***-0.649***	***0.0367***	***0.5164***	***-1.924***	***0.0561***	***0.0544***
98H	***0.915***	***0.0517***	***0.3603***	-5.804	0.0453	0.0005	-2.267	0.0366	0.0234	-4.176	0.0440	0.0005
98Z	***-0.204***	***0.0734***	***0.8387***	-2.669	0.0617	0.0076	-3.334	0.0521	0.0009	-3.800	0.0605	0.0005
55G+93F	-1.999	0.0710	0.0456	-3.670	0.0579	0.0005	***-1.452***	***0.0500***	***0.1464***	-4.126	0.0613	0.0005
27Z+29Z	***-0.427***	***0.0476***	***0.6691***	-3.682	0.0428	0.0005	-2.326	0.0368	0.0200	-2.991	0.0413	0.0028
25M+25Z+97E	-2.111	0.0744	0.0348	-1.953	0.0814	0.0508	***-1.706***	***0.0498***	***0.0881***	***-0.412***	***0.0827***	***0.6804***
15E+16J	***-0.123***	***0.0898***	***0.9019***	***-0.330***	***0.0677***	***0.7417***	***-1.847***	***0.0663***	***0.0648***	-3.182	0.0747	0.0015

Note. Effect sizes that are *not* statistically significant (p > .05) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
11B	-4.946	0.0188	0.0005	-2.195	0.0195	0.0282	***-1.349***	***0.0216***	***0.1773***	5000
11C	-4.163	0.0184	0.0005	-2.850	0.0189	0.0044	-2.303	0.0214	0.0213	5000
11H	-3.256	0.0187	0.0011	**-2.121**	0.0191	0.0339	-2.385	0.0217	0.0171	5000
11M	-4.085	0.0196	0.0005	-2.599	0.0198	0.0093	***-0.820***	***0.0219***	***0.4122***	4593
12B	-6.339	0.0181	0.0005	-2.429	0.0190	0.0152	***-1.631***	***0.0207***	***0.1028***	5000
12C	-5.974	0.0283	0.0005	***-0.531***	***0.0307***	***0.5953***	***-0.071***	***0.0313***	***0.9432***	1950
12F	***-1.156***	***0.0501***	***0.2477***	***-0.085***	***0.0506***	***0.9322***	***-1.773***	***0.0574***	***0.0762***	603
13B	-7.849	0.0180	0.0005	***-1.842***	***0.0191***	***0.0654***	-2.156	0.0206	0.0311	5000
13C	-4.072	0.0424	0.0005	***-1.700***	***0.0430***	***0.0892***	***-0.841***	***0.0522***	***0.4006***	720
13E	***-1.366***	***0.0292***	***0.1718***	-2.701	0.0293	0.0069	-3.844	0.0321	0.0005	1919
13F	***-1.170***	***0.0207***	***0.2420***	-3.329	0.0195	0.0009	-4.792	0.0222	0.0005	4101
13M	***-0.927***	***0.0491***	***0.3538***	***-0.538***	***0.0491***	***0.5907***	***-1.940***	***0.0556***	***0.0524***	776
13N	-2.722	0.0247	0.0065	***-1.049***	***0.0258***	***0.2943***	-4.352	0.0259	0.0005	2724
13R	***-1.382***	***0.0469***	***0.1669***	***-0.578***	***0.0497***	***0.5631***	***-0.912***	***0.0579***	***0.3618***	592
14D	***-0.922***	***0.0482***	***0.3566***	***1.466***	***0.0467***	***0.1427***	***-1.306***	***0.0556***	***0.1917***	683
16E	***-1.470***	***0.0483***	***0.1417***	***-0.470***	***0.0484***	***0.6385***	***-0.336***	***0.0511***	***0.7366***	703
16P	-4.051	0.0403	0.0005	***-1.877***	***0.0350***	***0.0605***	***-1.111***	***0.0459***	***0.2668***	1104
16R	-4.807	0.0286	0.0005	-3.451	0.0292	0.0006	***1.536***	***0.0295***	***0.1246***	1996
16S	-4.454	0.0251	0.0005	***-0.250***	***0.0277***	***0.8029***	-3.727	0.0320	0.0005	2406
19D	-4.915	0.0179	0.0005	-5.550	0.0189	0.0005	-4.267	0.0213	0.0005	5000
19E	-6.594	0.0182	0.0005	-3.528	0.0191	0.0005	-3.578	0.0216	0.0005	4764
19K	-8.257	0.0177	0.0005	-4.550	0.0185	0.0005	-2.693	0.0208	0.0071	5000
24Z	***-1.902***	***0.0488***	***0.0572***	-2.592	0.0529	0.0096	***-1.587***	***0.0562***	***0.1125***	752
25S	***-1.285***	***0.0612***	***0.1988***	-2.067	0.0652	0.0387	-2.548	0.0755	0.0108	358
27E	-3.761	0.0410	0.0005	***-1.351***	***0.0459***	***0.1767***	-2.845	0.0439	0.0044	898

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
29V	-3.018	0.0411	0.0025	***0.594***	***0.0450***	***0.5528***	-7.139	0.0477	0.0005	852
31C	-3.577	0.0181	0.0005	-7.692	0.0174	0.0005	-6.571	0.0211	0.0005	5000
31K	-6.634	0.0161	0.0005	-6.005	0.0177	0.0005	-4.343	0.0188	0.0005	5000
31L	-4.463	0.0224	0.0005	-3.591	0.0248	0.0005	-3.563	0.0254	0.0005	2778
31N	***-1.418***	***0.0438***	***0.1561***	-3.244	0.0438	0.0012	***-1.434***	***0.0490***	***0.1515***	709
31P	***-0.094***	***0.0508***	***0.9254***	-2.756	0.0584	0.0059	***-1.708***	***0.0546***	***0.0877***	563
31Q	-3.930	0.0313	0.0005	-5.029	0.0333	0.0005	***-1.437***	***0.0347***	***0.1507***	1394
31R	-5.343	0.0163	0.0005	-7.167	0.0175	0.0005	-5.538	0.0185	0.0005	5000
31S	***-0.430***	***0.0590***	***0.6674***	***-1.160***	***0.0676***	***0.2459***	-2.806	0.0729	0.0050	498
31V	-2.754	0.0189	0.0059	-6.231	0.0189	0.0005	-5.000	0.0208	0.0005	4278
35E	***-1.369***	***0.0384***	***0.1711***	***-0.943***	***0.0417***	***0.3458***	-2.000	0.0435	0.0455	1021
35H	***0.932***	***0.0753***	***0.3513***	***-0.753***	***0.0949***	***0.4512***	***-1.222***	***0.0911***	***0.2217***	307
35J	***-0.144***	***0.0365***	***0.8852***	-3.833	0.0386	0.0005	-5.444	0.0412	0.0005	1034
35N	***-1.758***	***0.0433***	***0.0788***	***-1.842***	***0.0457***	***0.0655***	-6.525	0.0466	0.0005	737
36M	-2.901	0.0332	0.0037	-2.459	0.0376	0.0140	***0.077***	***0.0338***	***0.9383***	1201
41C	***-1.064***	***0.0675***	***0.2872***	***-1.140***	***0.0669***	***0.2544***	-2.188	0.0598	0.0286	323
44B	***-1.769***	***0.0336***	***0.0769***	***-1.119***	***0.0370***	***0.2630***	-3.984	0.0391	0.0005	1045
44E	-3.851	0.0446	0.0005	-3.837	0.0468	0.0005	***0.015***	***0.0441***	***0.9881***	592
45B	-3.188	0.0469	0.0014	***-0.111***	***0.0491***	***0.9120***	-3.884	0.0487	0.0005	612
45D	***-1.771***	***0.0552***	***0.0765***	***-1.572***	***0.0544***	***0.1160***	***0.443***	***0.0543***	***0.6575***	565
45E	***-1.260***	***0.0589***	***0.2075***	-1.998	0.0577	0.0457	***0.504***	***0.0715***	***0.6145***	546
45K	***-1.320***	***0.0410***	***0.1868***	***-1.528***	***0.0467***	***0.1266***	-2.977	0.0474	0.0029	817
45L	-4.759	0.0551	0.0005	***0.624***	***0.0667***	***0.5325***	***-0.607***	***0.0632***	***0.5439***	448
45N	***-1.030***	***0.0478***	***0.3029***	-3.459	0.0532	0.0005	-3.489	0.0496	0.0005	563
45T	***0.512***	***0.0488***	***0.6084***	***-0.478***	***0.0544***	***0.6323***	-2.564	0.0562	0.0104	509

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
46Z	***-0.344***	***0.0524***	***0.7310***	***-0.770***	***0.0575***	***0.4414***	-2.142	0.0959	0.0322	498
51B	-5.305	0.0258	0.0005	-2.388	0.0281	0.0170	***-0.508***	***0.0310***	***0.6112***	2037
51K	-2.925	0.0521	0.0034	-3.059	0.0528	0.0022	***1.301***	***0.0569***	***0.1932***	532
51M	***-0.631***	***0.0656***	***0.5281***	-2.494	0.0751	0.0126	***-1.049***	***0.0813***	***0.2943***	327
51R	***-1.441***	***0.0424***	***0.1496***	-3.837	0.0462	0.0005	***-0.768***	***0.0492***	***0.4422***	723
51T	***1.938***	***0.0708***	***0.0526***	-2.294	0.0770	0.0218	***-1.405***	***0.0842***	***0.1600***	344
52C	***-1.306***	***0.0483***	***0.1916***	-5.324	0.0538	0.0005	***-1.408***	***0.0548***	***0.1592***	529
52D	-8.095	0.0143	0.0005	-13.013	0.0155	0.0005	***0.215***	***0.0160***	***0.8301***	5000
54B	-5.093	0.0306	0.0005	-3.915	0.0301	0.0005	***-1.772***	***0.0349***	***0.0764***	1380
55B	***-0.461***	***0.0222***	***0.6445***	-3.267	0.0252	0.0011	-4.650	0.0270	0.0005	2457
55D	***-1.588***	***0.0617***	***0.1122***	***1.039***	***0.0632***	***0.2989***	-3.301	0.0725	0.0010	415
57E	-2.777	0.0485	0.0055	***-1.069***	***0.0556***	***0.2850***	***1.187***	***0.0456***	***0.2351***	791
62B	-6.417	0.0197	0.0005	-6.412	0.0208	0.0005	***-1.180***	***0.0225***	***0.2381***	3054
62E	-4.098	0.0304	0.0005	***-1.840***	***0.0322***	***0.0658***	***-0.196***	***0.0375***	***0.8446***	1522
62F	-4.404	0.0460	0.0005	-3.635	0.0506	0.0005	***0.365***	***0.0587***	***0.7154***	527
62J	-3.924	0.0397	0.0005	-1.953	0.0417	0.0508	***-0.340***	***0.0452***	***0.7340***	887
63B	-10.031	0.0151	0.0005	-8.548	0.0166	0.0005	***1.424***	***0.0177***	***0.1544***	5000
63D	-4.154	0.0346	0.0005	-2.621	0.0349	0.0088	-3.423	0.0361	0.0006	1234
63E	-2.703	0.0308	0.0069	-6.406	0.0311	0.0005	***-1.201***	***0.0366***	***0.2296***	1376
63G	***-0.866***	***0.0475***	***0.3865***	-2.729	0.0474	0.0064	***-0.509***	***0.0506***	***0.6109***	785
63H	-3.913	0.0245	0.0005	***-1.213***	***0.0266***	***0.2252***	-5.005	0.0293	0.0005	2396
63J	-3.613	0.0347	0.0005	***-0.530***	***0.0378***	***0.5964***	***-1.526***	***0.0377***	***0.1270***	1302
63N	-4.274	0.0406	0.0005	***-1.488***	***0.0452***	***0.1369***	***0.077***	***0.0441***	***0.9387***	750
63S	-4.210	0.0243	0.0005	-4.134	0.0260	0.0005	-4.055	0.0255	0.0005	2506
63T	-3.341	0.0226	0.0008	-5.619	0.0228	0.0005	-2.042	0.0228	0.0412	3378

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
63W	-9.242	0.0195	0.0005	-5.906	0.0208	0.0005	-2.514	0.0222	0.0119	3062
63Y	-3.452	0.0406	0.0006	-2.588	0.0380	0.0097	-1.956	0.0386	0.0505	987
67N	-2.595	0.0358	0.0095	***-0.941***	***0.0348***	***0.3465***	-4.573	0.0389	0.0005	1359
67R	-3.444	0.0807	0.0006	***0.155***	***0.0782***	***0.8771***	***-1.616***	***0.0863***	***0.1062***	236
67T	-3.432	0.0325	0.0006	-2.792	0.0326	0.0052	-3.834	0.0354	0.0005	1564
67U	-3.412	0.0314	0.0006	-2.633	0.0311	0.0085	-2.803	0.0334	0.0051	1632
67V	-4.686	0.0346	0.0005	-2.635	0.0336	0.0084	***-1.762***	***0.0377***	***0.0781***	1751
67Y	-3.933	0.0386	0.0005	-3.973	0.0402	0.0005	***-1.924***	***0.0429***	***0.0544***	1168
68B	***-0.228***	***0.0614***	***0.8193***	1.956	0.0640	0.0505	-3.564	0.0626	0.0005	640
68D	***-0.826***	***0.0532***	***0.4087***	***1.290***	***0.0570***	***0.1972***	-4.497	0.0518	0.0005	740
68F	***-1.583***	***0.0494***	***0.1135***	-2.218	0.0500	0.0266	***-1.806***	***0.0458***	***0.0708***	712
68G	-2.195	0.0435	0.0282	-2.587	0.0444	0.0097	***-0.772***	***0.0477***	***0.4403***	904
68J	***0.438***	***0.0387***	***0.6613***	-2.638	0.0388	0.0083	-3.027	0.0414	0.0025	1128
68M	-2.195	0.0654	0.0282	***-1.718***	***0.0656***	***0.0858***	***-0.995***	***0.0648***	***0.3197***	388
68N	***-0.460***	***0.0507***	***0.6457***	***-1.715***	***0.0583***	***0.0864***	-3.864	0.0591	0.0005	475
68Z	***-1.223***	***0.0425***	***0.2213***	***-0.657***	***0.0431***	***0.5111***	-3.831	0.0418	0.0005	749
71D	***-0.759***	***0.0290***	***0.4478***	***-1.772***	***0.0304***	***0.0764***	-6.404	0.0426	0.0005	1431
71G	3.966	0.0328	0.0005	-2.469	0.0358	0.0136	-6.110	0.0392	0.0005	1145
71L	***-0.746***	***0.0164***	***0.4559***	***1.801***	***0.0176***	***0.0717***	-11.805	0.0198	0.0005	5000
71M	***-1.083***	***0.0359***	***0.2787***	***1.444***	***0.0420***	***0.1487***	-6.683	0.0477	0.0005	972
72E	-3.895	0.0296	0.0005	-2.613	0.0324	0.0090	***-1.561***	***0.0344***	***0.1185***	1651
72G	***-1.764***	***0.0292***	***0.0778***	-2.838	0.0310	0.0045	-2.340	0.0365	0.0193	1738
73C	***0.230***	***0.0247***	***0.8184***	***1.210***	***0.0277***	***0.2264***	-6.937	0.0276	0.0005	2246
73D	***1.567***	***0.0486***	***0.1171***	***-0.627***	***0.0562***	***0.5305***	-2.484	0.0741	0.0130	500
74B	***0.589***	***0.0360***	***0.5560***	-2.711	0.0358	0.0067	-8.044	0.0415	0.0005	1184

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
75B	***-0.858***	***0.0170***	***0.3911***	***-1.487***	***0.0186***	***0.1370***	-8.575	0.0195	0.0005	4113
75C	***1.521***	***0.0224***	***0.1282***	***-1.210***	***0.0259***	***0.2264***	-6.717	0.0254	0.0005	2505
75D	***0.492***	***0.0221***	***0.6229***	-2.878	0.0250	0.0040	-4.429	0.0255	0.0005	2714
75E	2.521	0.0283	0.0117	-2.884	0.0325	0.0039	-6.911	0.0356	0.0005	1379
75F	***1.633***	***0.0468***	***0.1024***	3.045	0.0477	0.0023	-3.418	0.0609	0.0006	624
76J	***1.508***	***0.0374***	***0.1317***	***-0.116***	***0.0384***	***0.9073***	-5.536	0.0378	0.0005	997
76P	***-0.097***	***0.0214***	***0.9230***	-4.117	0.0239	0.0005	-4.419	0.0237	0.0005	2897
76V	-6.578	0.0166	0.0005	-4.822	0.0182	0.0005	-5.299	0.0187	0.0005	5000
76X	-2.989	0.0459	0.0028	***-1.635***	***0.0509***	***0.1020***	-3.801	0.0577	0.0005	541
77F	-6.199	0.0163	0.0005	-4.808	0.0174	0.0005	-2.366	0.0185	0.0180	5000
77W	-4.175	0.0432	0.0005	***-1.309***	***0.0456***	***0.1907***	***-0.755***	***0.0428***	***0.4501***	805
81L	***0.289***	***0.0709***	***0.7726***	***-0.444***	***0.0834***	***0.6570***	***0.626***	***0.0749***	***0.5312***	331
82C	***-1.485***	***0.0419***	***0.1376***	***-1.877***	***0.0414***	***0.0605***	***-0.505***	***0.0452***	***0.6134***	808
88H	***0.386***	***0.0307***	***0.6998***	***-1.508***	***0.0348***	***0.1314***	***-1.610***	***0.0369***	***0.1074***	1525
88M	-6.270	0.0173	0.0005	-4.047	0.0185	0.0005	-3.251	0.0195	0.0012	5000
88N	***1.722***	***0.0294***	***0.0850***	***-0.163***	***0.0313***	***0.8709***	-5.459	0.0291	0.0005	1954
91A	-6.265	0.0180	0.0005	-2.637	0.0188	0.0084	-4.288	0.0212	0.0005	5000
91D	***-0.694***	***0.0435***	***0.4875***	***-0.683***	***0.0484***	***0.4949***	***-1.269***	***0.0498***	***0.2045***	748
91E	***-0.802***	***0.0377***	***0.4228***	***-1.180***	***0.0367***	***0.2378***	-3.951	0.0434	0.0005	1209
91F	***0.246***	***0.0649***	***0.8059***	***0.256***	***0.0740***	***0.7983***	***-1.047***	***0.0735***	***0.2951***	474
91G	-2.541	0.0682	0.0111	***-0.985***	***0.0640***	***0.3247***	***-1.315***	***0.0923***	***0.1887***	309
91K	***0.730***	***0.0339***	***0.4656***	-3.708	0.0375	0.0005	***-0.530***	***0.0389***	***0.5960***	1478
91M	***1.005***	***0.0551***	***0.3151***	-2.177	0.0556	0.0295	-4.236	0.0660	0.0005	513
91P	***-0.485***	***0.0486***	***0.6274***	***0.043***	***0.0506***	***0.9658***	***-0.836***	***0.0628***	***0.4031***	695
91Q	-3.173	0.0447	0.0015	***-0.851***	***0.0470***	***0.3946***	***-1.586***	***0.0522***	***0.1127***	682

Note. Effect sizes that are *not* statistically significant ($p > .05$) are bold and italicized.

Table 5 (cont'd)

	ASVAB Subtest									
	MC			EI			VE			
JF	*t*	*SE*	*p*	*t*	*SE*	*p*	*t*	*SE*	*p*	*N*
91R	***-1.926***	*0.0466*	***0.0540***	-2.257	0.0501	0.0240	***-0.893***	***0.0577***	***0.3718***	558
91S	-3.409	0.0585	0.0007	-3.031	0.0532	0.0024	***-0.104***	***0.0581***	***0.9173***	514
91T	***1.573***	***0.0726***	***0.1157***	***-0.288***	***0.0725***	***0.7735***	-2.727	0.0748	0.0064	345
91Z	-2.522	0.0491	0.0117	***-0.626***	***0.0528***	***0.5312***	-3.645	0.0581	0.0005	641
92A	-5.155	0.0162	0.0005	***0.329***	***0.0175***	***0.7424***	-6.250	0.0194	0.0005	5000
92G	-5.573	0.0166	0.0005	-4.724	0.0174	0.0005	-6.880	0.0189	0.0005	5000
92M	***-1.108***	***0.0612***	***0.2680***	***0.080***	***0.0842***	***0.9361***	***-0.499***	***0.0764***	***0.6175***	298
92R	-2.575	0.0408	0.0100	***-1.119***	***0.0429***	***0.2633***	***1.109***	***0.0463***	***0.2676***	1009
92Y	***0.658***	***0.0167***	***0.5106***	-2.801	0.0182	0.0051	-6.888	0.0186	0.0005	5000
93C	***0.569***	***0.0524***	***0.5695***	-3.176	0.0555	0.0015	-4.373	0.0648	0.0005	626
93P	-3.856	0.0299	0.0005	-2.634	0.0296	0.0084	-8.996	0.0324	0.0005	1327
95B	-5.873	0.0182	0.0005	-2.708	0.0181	0.0068	-6.927	0.0224	0.0005	5000
95C	***-0.879***	***0.0687***	***0.3794***	***-0.288***	***0.0731***	***0.7736***	***-0.741***	***0.0649***	***0.4588***	323
96B	-2.519	0.0388	0.0118	***0.072***	***0.0411***	***0.9423***	-6.065	0.0559	0.0005	818
96D	***-1.803***	***0.0558***	***0.0714***	***0.211***	***0.0600***	***0.8326***	-2.732	0.0761	0.0063	361
96R	-2.089	0.0383	0.0367	***-0.920***	***0.0424***	***0.3576***	-4.064	0.0447	0.0005	792
97B	***-1.471***	***0.0578***	***0.1413***	-2.155	0.0618	0.0312	-2.879	0.0924	0.0040	429
98C	***-1.660***	***0.0532***	***0.0969***	***-1.003***	***0.0525***	***0.3156***	-3.651	0.0783	0.0005	562
98G	***-1.098***	***0.0417***	***0.2724***	***-1.415***	***0.0415***	***0.1572***	***-1.261***	***0.0664***	***0.2074***	1242
98H	***-0.810***	***0.0406***	***0.4178***	***0.880***	***0.0451***	***0.3786***	-2.424	0.0508	0.0153	966
98Z	***-1.297***	***0.0578***	***0.1946***	***0.735***	***0.0597***	***0.4622***	-2.987	0.0752	0.0028	463
55G+93F	***-0.629***	***0.0516***	***0.5296***	***0.229***	***0.0604***	***0.8189***	***0.739***	***0.0551***	***0.4602***	518
27Z+29Z	-2.623	0.0389	0.0087	-1.955	0.0410	0.0505	-3.575	0.0418	0.0005	981
25M+25Z+97									***0.1558***	
E	-2.054	0.0583	0.0400	***-0.163***	***0.0558***	***0.8706***	***-1.419***	***0.0942***		1195
15E+16J	***-1.514***	***0.0773***	***0.1299***	***-1.440***	***0.0802***	***0.1499***	***1.042***	***0.0787***	***0.2973***	395

Note. Effect sizes that are *not* statistically significant (p > .05) are bold and italicized.

APPENDIX B: DIFFERENCES IN PREDICTED PERFORMANCE SCORES BY JOB FAMILY

Table 1

Differences in Predicted Performance Scores by Job Family (9 Job Family Configuration)

Job Family	CL	CO	EL	FA	GM	MM	OF	SC	ST
CL	--								
CO	3.892015	--							
EL	2.618116	1.740430	--						
FA	2.628248	0.264133	0.822471	--					
GM	5.002585	2.218514	0.532043	1.418907	--				
MM	12.441890	6.422752	3.911620	5.675906	1.945890	--			
OF	4.010194	1.267411	0.397983	0.669862	0.325321	2.739432	--		
SC	1.415567	1.377832	0.332201	0.584810	1.462565	6.256495	1.041342	--	
ST	1.167606	2.099922	0.414195	0.976016	1.710522	6.510473	1.169328	0.266785	--

Note. Variances of composite differences are express in percentage (i.e., multiplied by 100).

Table 2

Differences in Predicted Performance Scores by Job Family (17 Job Family Configuration)

Job Family	CL1	CL2	CO1	CO2	EL1	EL2	EL3	FA
CL1	--							
CL2	1.735836	--						
CO1	8.021002	3.087820	--					
CO2	6.237076	1.620892	1.542914	--				
EL1	6.669339	2.041411	3.081634	0.354608	--			
EL2	5.329273	1.395066	2.849379	0.296286	0.242457	--		
EL3	2.279515	0.676620	4.774335	1.712869	1.458464	1.096957	--	
FA	5.379435	1.189068	0.847776	0.216697	0.983075	0.715687	1.911736	--
GM1	9.672718	4.447639	7.132130	2.196940	1.133051	1.373711	3.109155	3.543209
GM2	8.131839	2.626738	1.634354	0.194105	0.567426	0.598965	2.863516	0.530867
MM1	20.242374	11.222096	9.739843	5.294465	4.021937	5.386637	9.673917	7.178008
MM2	7.221701	2.816097	5.353999	1.277207	0.491684	0.746706	1.707696	2.157375
OF	7.230601	2.113780	2.417866	0.216284	0.204383	0.466532	1.959067	0.669862
SC	3.433732	0.529240	2.387426	0.576138	0.745359	0.338988	0.624314	0.584810
ST1	4.408539	0.861110	1.278158	0.374138	1.037940	0.832985	1.247799	0.194635
ST2	1.420300	0.912740	6.183152	2.874471	2.636458	1.997892	0.217716	2.924776
ST3	3.586894	1.002068	4.407834	1.086538	0.764826	0.455383	0.284409	1.466942

Note. Variances of composite differences are express in percentage (i.e., multiplied by 100).

Table 2 (cont'd)

Differences in Predicted Performance Scores by Job Family (17 Job Family Configuration)

Composite	GM1	GM2	MM1	MM2	OF	SC	ST1	ST2	ST3
CL1									
CL2									
CO1									
CO2									
EL1									
EL2									
EL3									
FA									
GM1	--								
GM2	2.085484	--							
MM1	2.751210	3.599278	--						
MM2	0.629146	3.887209	0.739252	--					
OF	1.475475	8.023234	1.603940	1.041342	--				
SC	2.811299	8.147930	2.224060	0.834249	0.480994	--			
ST1	3.758731	12.012069	2.581212	3.220391	1.289976	0.480994	--		
ST2	4.291467	7.219999	0.726863	1.169385	0.481461	1.289976	2.137008	--	
ST3	1.853602	3.599278	0.739252	1.041342	0.480994	0.481461	1.188982	0.684657	--

Note. Variances of composite differences are express in percentage (i.e., multiplied by 100).

Table 3

Expected Reduction in Total R-Squared (R^2) from Combining Job Families

Job Family	CL1	CL2	CO1	CO2	EL1	EL2	EL3	FA
CL1	--							
CL2	.0455	--						
CO1	.2719	.1494	--					
CO2	.1828	.0641	.0928	--				
EL1	.1345	.0501	.0961	.0097	--			
EL2	.0980	.0306	.0772	.0071	.0043	--		
EL3	.0274	.0091	.0727	.0244	.0170	.0121	--	
FA	.1348	.0383	.0378	.0080	.0231	.0151	.0251	--
GM1	.1554	.0833	.1595	.0445	.0175	.0197	.0316	.0643
GM2	.1415	.0540	.0409	.0044	.0095	.0092	.0306	.0105
MM1	.5819	.4323	.5635	.2417	.1076	.1277	.1363	.2591
MM2	.1005	.0447	.0985	.0217	.0066	.0094	.0158	.0333
OF	.2301	.0935	.1737	.0117	.0060	.0120	.0290	.0275
SC	.0611	.0112	.0617	.0133	.0127	.0053	.0068	.0119
ST1	.1067	.0265	.0537	.0132	.0237	.0171	.0161	.0057
ST2	.0302	.0239	.2096	.0842	.0532	.0367	.0026	.0733
ST3	.0893	.0320	.1944	.0398	.0179	.0096	.0037	.0443

Note. Variances of composite differences are express in percentage (i.e., multiplied by 100).

Table 3 (cont'd)

Expected Reduction in Composite Validity (R^2) from Combining Job Families

Composite	GM1	GM2	MM1	MM2	OF	SC	ST1	ST2	ST3
CL1									
CL2									
CO1									
CO2									
EL1									
EL2									
EL3									
FA									
GM1	--								
GM2	.0287	--							
MM1	.0550	.0904	--						
MM2	.0072	.0184	.0603	--					
OF	.0316	.0070	.2023	.0131	--				
SC	.0394	.0188	.1825	.0198	.0257	--			
ST1	.0665	.0194	.2801	.0336	.0324	.0095	--		
ST2	.0690	.0743	.3452	.0359	.1025	.0230	.0517	--	
ST3	.0335	.0368	.2581	.0112	.0475	.0098	.0345	.0170	--

Note. Variances of composite differences are express in percentage (i.e., multiplied by 100).

APPENDIX C: SAS PROGRAMS FOR RUNNING K-FOLD DOUBLE CROSS-VALIDATION DESIGN FOR ESTIMATING MPP

```
/*****************************************************************************

Program applying the MPP K-Fold Validation macro program ...

*****************************************************************************/

options formchar='|-++++++' nodate nonumber;

/* *** EDIT AS NEEDED *** Input data library */
libname kfvLib "D:\NEW AA\SAS Workspace\KFVPGMDISTN\InputData";
/* *** EDIT AS NEEDED *** Output data library */
libname mppsim "D:\NEW AA\SAS Workspace\KFVPGMDISTN\MmmSimData";


/* Include OPJM K-Fold Validation macros */
%let PRINT=OFF;
/* *** EDIT AS NEEDED *** Directory where programs are located */
filename KFVPGM 'D:\NEW AA\SAS Workspace\KFVPGMDISTN\Programs';
%include KFVPGM(CreateSampleABC);
%include KFVPGM(ComputeDescriptives);
%include KFVPGM(Step1A_correction_unreliability_KFV);
%include KFVPGM(Step1B_correction_range-restriction_KFV);
%include KFVPGM(Step2_JF_Validities_KFV);
%include KFVPGM(Step3_Best_Positive_Weights_KFV);
%include KFVPGM(Step4&5_b_to_uk_values_KFV);
%include KFVPGM(ComputeCriterionScores);
%include KFVPGM(OptimalAssignmetPredictedScores);
%include KFVPGM(KFoldEvalMpp);


/* *** EDIT AS NEEDED *** Dump log output to file ... */
%let RUNLOG="D:\NEW AA\SAS
Workspace\KFVPGMDISTN\MmmSimData\RUN_KFoldEvalMpp_02022004.TXT";
proc printto log=&RUNLOG;run;


/* *** EDIT AS NEEDED *** PREFIX of output files */
%let RUNPREFFNAME=YPP;

/* *** EDIT AS NEEDED *** Random seed.
*/
/* NOTE: Use SAME SEED for all simulation configuration to do paired
comparisons */
%let RUNSEED=1001;


/* *** Edit RUNx macro vars in %LET STATEMENTS to specify simulation problem
parameters */

%let RUNREPSTART=1;
%let RUNREPEND=49;

/** JF=9 , UNEQUAL Variance **/

%let RUNJF=JF9;
```

```
%let RUNBETACONSTRAINT=NONE;    /* POSITIVE1=JZV, POSITIVE2=HumRRO, NONE=LSE
*/
%let RUNTIER=TIER1;                   /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
/*
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);
*/

%let RUNJF=JF9;
%let RUNBETACONSTRAINT=POSITIVE1;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER1;                   /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

%let RUNJF=JF9;
%let RUNBETACONSTRAINT=POSITIVE2;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER1;                   /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

/** JF=9 , EQUAL Variance **/

%let RUNJF=JF9;
%let RUNBETACONSTRAINT=NONE;    /* POSITIVE1=JZV, POSITIVE2=HumRRO, NONE=LSE
*/
%let RUNTIER=TIER2;                   /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
/*
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);
*/

%let RUNJF=JF9;
%let RUNBETACONSTRAINT=POSITIVE1;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
```

```
%let RUNTIER=TIER2;                    /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

%let RUNJF=JF9;
%let RUNBETACONSTRAINT=POSITIVE2;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER2;                    /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);


/** JF=17 , UNEQUAL Variance **/

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=NONE;    /* POSITIVE1=JZV, POSITIVE2=HumRRO, NONE=LSE
*/
%let RUNTIER=TIER1;                    /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
/*
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);
*/

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=POSITIVE1;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER1;                    /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=POSITIVE2;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER1;                    /* TIER1=unequal variance, TIER2=equal
variance */
```

```
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
```

```
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

/** JF=17 , EQUAL Variance **/

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=NONE;    /* POSITIVE1=JZV, POSITIVE2=HumRRO, NONE=LSE
*/
%let RUNTIER=TIER2;                  /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
/*
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);
*/

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=POSITIVE1;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER2;                  /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);

%let RUNJF=JF17;
%let RUNBETACONSTRAINT=POSITIVE2;    /* POSITIVE1=JZV, POSITIVE2=HumRRO,
NONE=LSE */
%let RUNTIER=TIER2;                  /* TIER1=unequal variance, TIER2=equal
variance */
%let
RUNFNAME=&RUNPREFFNAME._&RUNJF._&RUNBETACONSTRAINT._&RUNTIER._&RUNREPSTART._&
RUNREPEND;
proc datasets library=mppsim; delete &RUNFNAME; quit; run;
%KFoldEvalMPP(mppsim.&RUNFNAME,&RUNSEED,&RUNJF,&RUNBETACONSTRAINT,&RUNTIER,&R
UNREPSTART,&RUNREPEND);


/* RESET PROC PRINTO */
proc printto;run;
```

```
/*****************************************************************************

Program that partitions the data into samples A(PP), B(AA), and C(Cross)

*** REQUIRED IN SIMULATION ***

*****************************************************************************/

/* Initialize total number of MOS */
data _null_;
  set kfvLib.entrymos155 nobs=numMOS;
  put numMOS=numMOS;
  call symput('NUMMOS',numMOS);
  stop;
run;


/* read MOS sample size in Army input data */
%macro ReadMOSsizeArray;
  array asizeN{&NUMMOS} _temporary_;
  array asizeC{&NUMMOS} _temporary_;
  do i=1 to &NUMMOS;
    set kfvLib.entrymos155 (keep = mosnumid obsN obsC);
    asizeN{mosnumid} = obsN;
    asizeC{mosnumid} = obsC;
  end;
  drop obsC obsN;
%mend;


/* partition the data into 3 parts: sampleDataA sampleDataB sampleDataC */
%macro CreateSampleABC(IREP,REPSEED,NREPSAMPLEC);
data SamplePartition;
  %ReadMOSsizeArray;
  do mosnumid=1 to &NUMMOS;
    sizeC = asizeC{mosnumid};
    id = 0;
    do i=1 to asizeN{mosnumid};
      id+1;
      inC = ( (&IREP-1)*sizeC < i <= (&IREP)*sizeC );
      if (^inC) then
        randToSort = 1+uniform(&REPSEED);
      else
        randToSort = -(1+uniform(&REPSEED));
      output;
    end;
  end;
  drop sizeC i inC;
run;
proc sort data=SamplePartition;
  by mosnumid randToSort;
run;
data SamplePartition;
  %ReadMOSsizeArray;
  do mosnumid=1 to &NUMMOS;
    sizeOverallC+asizeC{mosnumid};
```

```
  end;
  retain sizeA sizeC;
  do while(^last);
    set SamplePartition end=last;
    by mosnumid;
    if first.mosnumid then do;
      sizeC = asizeC{mosnumid};
      sizeA = round((asizeN{mosnumid}-sizeC)/2);
      nA = 0;
    end;
    if (randToSort<0) then do;
      /* next two line cycle from: 1,2,3,4,&NREPSAMPLEC */
      irepc = mod(irepc,&NREPSAMPLEC);
      irepc+1;
      sampleID = 'C'||left(put(irepc,2.));
    end;
    else if ( nA < sizeA) then do;
      sampleID = 'A';
      nA+1;
    end;
    else
      sampleID = 'B';
    output;
  end;
  keep mosnumid id sampleID;
run;
proc sort data=SamplePartition;
  by mosnumid id;
run;
data sampleDataA sampleDataB
  %do ISAMPLEC=1 %to &NREPSAMPLEC;
    sampleDataC&ISAMPLEC
  %end;
;
  merge kfvLib.kfvArmyInput SamplePartition;
  by mosnumid id;
  if (sampleID='A') then
    output sampleDataA;
  else if (sampleID='B') then
    output sampleDataB;
  %do ISAMPLEC=1 %to &NREPSAMPLEC;
    else if (sampleID="C&ISAMPLEC") then
      output sampleDataC&ISAMPLEC;
  %end;
run;
%mend;
```

```
/******************************************************************************

Compute descriptives, correlations, and covariances for samples A(PP), B(AA)

*** REQUIRED IN SIMULATION ***

******************************************************************************/

%macro ComputeDescriptives(SAMPLEDATA,MEANDATA,CORRDATA,COVDATA,COVDATA_ALL);

proc means data=&SAMPLEDATA noprint;
  var GS AR NO CS AS MK MC EI VE SQT;
  by mosnumid;
  output out=tmp;
run;
proc transpose data=tmp
               out=&MEANDATA (keep= mosnumid _name_ mean std
                         rename= (_name_=names std=sd));
  var GS AR NO CS AS MK MC EI VE SQT;
  id _stat_;
  by mosnumid;
run;

proc corr data=&SAMPLEDATA noprint
          outp=&CORRDATA (where=(_type_='CORR')
                    rename=(_name_=names));
  var GS AR NO CS AS MK MC EI VE SQT;
  by mosnumid;
run;

proc corr data=&SAMPLEDATA noprint cov
          outp=&COVDATA (where=(_type_='COV')
                    rename=(_name_=names));
  var GS AR NO CS AS MK MC EI VE SQT;
  by mosnumid;
run;

proc corr data=&SAMPLEDATA noprint cov
          outp=&COVDATA_ALL (where=(_type_='COV')
                    rename=(_name_=names));
  var GS AR NO CS AS MK MC EI VE SQT;
run;

%mend;
```

```
/*************************************************************************

 Correcting ASVAB-SQT validity coefficients and covariances
 for criterion unreliability

 OUTPUT DATASETS: Ryx_CorrectRelib, Cyx_CorrectRelib_MOS
 INPUT DATASETS: Descriptive_MOS, R_Samp_MOS, Info_MOS

*** REQUIRED IN SIMULATION ***

*************************************************************************/


%macro CorrectUnreliability(Ryx_CorrectRelib_MOS,Cyx_CorrectRelib_MOS,
                            Descriptive_MOS,R_Samp_MOS,Info_MOS);

/* variable names for ASVAB subtests                                */
%let TESTNAMES=GS AR NO CS AS MK MC EI VE;

proc iml;

  TestNames = {&TESTNAMES};

  /* Read ASVAB-SQT correlations and numeric ID into XYcorr and MOSNumID */
  use &R_Samp_MOS;
  read all var(TestNames) where(NAMES="SQT") into XYcorr;
  read all var{MOSNUMID} where(NAMES="SQT") into MOSNumID;
  close &R_Samp_MOS;

  /* Read SQT reliabilities into vector YYscal*/
  use &Info_MOS;
  read all var{RelYY} into YYscal;
  close &Info_MOS;

  NumMOS = nrow(MosNumID);     /* =nrow(CorMat) */
  NumTest =ncol(TestNames);

  /* correcting validity coefficients for attenuation using standard formula
*/
  correctedRxy = XYcorr#(1/SQRT(YYscal));

  /* initialize corrected covariance matrix */
  correctedCVxy = repeat(0,NumMOS,NumTest);

  /* computing corrected covariances -- one ASVAB subtest column at a time */
  use &Descriptive_MOS;
  read all var{SD} where(names="SQT") into sdY;
  do iTest = 1 to NumTest;
    xName = TestNames[iTest];
    read all var{SD} where(NAMES=xName) into sdX;
    correctedCVxy[,iTest] = correctedRxy[,iTest]#sdY#sdX;
  end;
  close &Descriptive_MOS;

  /* creating dataset of MOS corrected SQT-ASVAB correlations */
  create &Ryx_CorrectRelib_MOS var{MOSNUMID &TESTNAMES};
```

```
  correctedRxy = MosNumID || correctedRxy;
  append from correctedRxy;
  close &Ryx_CorrectRelib_MOS;

  /* creating dataset of MOS corrected SQT-ASVAB covariances */
  create &Cyx_CorrectRelib_MOS var{MOSNUMID &TESTNAMES};
  correctedCVxy = MosNumID || correctedCVxy;
  append from correctedCVxy;
  close &Cyx_CorrectRelib_MOS;

quit;
run;

%mend;
```

```
/**************************************************************************

 Correcting ASVAB-SQT validity coefficients and covariances for
 range restriciton.

 OUTPUT DATASETS: Ryx_CorrectRelibRange_MOS
 INPUT DATASETS: C_RefPop,C_Samp_MOS,Cyx_CorrectRelib_MOS

*** REQUIRED IN SIMULATION ***
**************************************************************************/


%macro CorrectRangeRestriction(Ryx_CorrectRelibRange_MOS,
                               C_RefPop,C_Samp_MOS,Cyx_CorrectRelib_MOS);

/* variable names for ASVAB subtests */
%let TESTNAMES=GS AR NO CS AS MK MC EI VE;

proc iml;

  TestNames = {&TESTNAMES};

  /* read REFERENCE POPULATION ASVAB subtests covariance */
  use &C_RefPop;
  read all var{&TESTNAMES} where(_TYPE_='COV' & names?TestNames) into PopCxx;
  close &C_RefPop;
  SDx = sqrt(vecdiag(PopCxx));

  /* open MOS SQT-ASVAB covariance corrected for unreliability */
  use &Cyx_CorrectRelib_MOS;
  read all var{MOSNUMID} into MosNumID;
  NumMOS = nrow(MosNumID);

  /* open MOS SQT-ASVAB sample variance-covariance -- no correction */
  use &C_Samp_MOS;

  /* create output data for range-restriction corrected validities */
  create &Ryx_CorrectRelibRange_MOS var{MOSNUMID &TESTNAMES};

  /*looping through MOSs listed under MOSTextID*/
  do idxMOS=1 to NumMOS;

    /* read reliability corrected ASVAB-SQT covariance, uncorrected ASVAB
       variance-covariance, and uncorrected SQT variance from iTH MOS     */
    setin &Cyx_CorrectRelib_MOS;
    read all var{&TESTNAMES} where(MOSNUMID=idxMOS) into Cxc; *correctedCVxy;
    setin &C_Samp_MOS;
    read all var{&TESTNAMES} where(names?TestNames & MOSNUMID=idxMOS) into
Cxx;
    read all var{SQT} where(names='SQT' & MOSNUMID=idxMOS) into Cyy;

    /* compute range-restriction corrected ASVAB-SQT covariances for iTH MOS
*/
    PopCxc = PopCxx*inv(Cxx)*Cxc`;
    PopCcc = Cyy+Cxc*inv(Cxx)*(PopCxc-Cxc`);
```

```
    /* compute range-restriction corrected ASVAB-SQT correlations for iTH
MOS*/
    PopRxc = (1/SDx/*Sxvec*/)#(PopCxc)#(1/sqrt(PopCcc));

    /* append iTH MOS SQT-ASVAT correlations to output data */
    TmpOutput = idxMOS || PopRxc`;
    setout &Ryx_CorrectRelibRange_MOS;
    append from TmpOutput;

  end;

  close &Cyx_CorrectRelib_MOS;
  close &C_Samp_MOS;
  close &Ryx_CorrectRelibRange_MOS;

quit;
run;

%mend;
```

```
/*****************************************************************************

 Aggregating corrected ASVAB-SQT validity coefficients by job family.

*** REQUIRED IN SIMULATION ***

*****************************************************************************/

%macro
JFValid(JF_VALIDITY_DATA,MOS_VALIDITY_DATA,JF_SOLUTION,JF_CONFIG_DATA);

/* variable names for ASVAB subtests */
%let TESTNAMES=GS AR NO CS AS MK MC EI VE;

proc iml;

  /* open data containing Job Family MOS configuration */
  use &JF_CONFIG_DATA;
  read all var{&JF_SOLUTION} into JFSolVec;

  /* Total number of JF in JFSolVec vector */
  NumJF = max(JFSolVec);

  /* open data containing reference population MOS validities */
  use &MOS_VALIDITY_DATA;

  /* create output data set for aggregated JF validities */
  create  &JF_VALIDITY_DATA var{&JF_SOLUTION &TESTNAMES};
  setout &JF_VALIDITY_DATA;

  do idxJF = 1 to NumJF;

    /* locate MOS in iTH job family and read acquisition weights */
    setin &JF_CONFIG_DATA;
    MOSJFIDX = loc(JFSolVec=idxJF);
    read point(MOSJFIDX) var{AcqN} into N_Wgt;

    /* read corrected validities of MOSs in iTH job family */
    setin &MOS_VALIDITY_DATA;
    read point(MOSJFIDX) var{&TESTNAMES} into XYvec;

    /* aggregate validity coefficients across MOS weighted by N         */
    /* - note job family index is concatenated to output validity vector */
    JFCorr = idxJF || (diag(N_Wgt)*XYvec)[+,]/sum(N_Wgt);

    append from JFCorr;

    end;

  close &JF_CONFIG_DATA;
  close &MOS_VALIDITY_DATA;
  close &JF_VALIDITY_DATA;

quit;
run;
%mend;
```

```
/*****************************************************************************

 Computing Beta Weights by job family.
 * Use macro argument CONSTRAINT to obtain different solutions:
        NONE = no constraint on subtest weights
   POSITIVE1 = Postive weights using Zeidner-Johnson-Vladimirsky stopping
rule
   POSITIVE2 = Postive weights -- ignoring solutions with negative weights

*** REQUIRED IN SIMULATION ***

*****************************************************************************/

%macro BetaWeights(BETADATA,COVDATA,VALIDITYDATA,JFSOLUTION,CONSTRAINT);

/* variable names for ASVAB subtests, excluding NO and CS */
%let TESTNAMES=GS AR AS MK MC EI VE;

%let CORRDATA=TMPCORRDATA;

proc iml;
  TestNames = {&TESTNAMES SQT};
  NTests = ncol(TestNames);
  _TYPE_={"MEAN","STD","N"}//j(NTests,1,"CORR");
  _NAME_=j(3,1,"")//t(TestNames);

  call symput('MNTESTS',char(NTests));

  /* Used later for CONSTRAINT=POSITIVE */
  call symput('MNTESTS_ASVAB',char(NTests-1));

  do i=1 to NTests;
    if(i<10) then
        MTESTNAME = concat('MTESTNAME',char(i,1,0));
    else
        MTESTNAME = concat('MTESTNAME',char(i,2,0));
    call symput(MTESTNAME,TestNames[i]);
  end;

  use &COVDATA;
  read all var{&TESTNAMES} where((Names?TestNames) & (Names^?"SQT")) into
RXX;
  close &COVDATA;

  SXX_INV = sqrt(diag(1/RXX));
  RXX = SXX_INV*RXX*SXX_INV;

  XMEAN = j(1,NTests,0);
  XSTD  = j(1,NTests,1);

  /* NOT actual sample sizes, but does not matter for estimation */
  XN    = j(1,NTests,10000);

  /* Read Validity Data Matrix -- Note that MOS/JF<->Row */
  use &VALIDITYDATA;
  read all var{&TESTNAMES} into RXY_ALL;
```

```
  read all var{&JFSOLUTION} into JFNO_ALL;
  close &VALIDITYDATA;

  /* For each job family, read validities and create correlation matrix */
  create &CORRDATA(Type=corr) var ({ &JFSOLUTION _TYPE_ _NAME_}||TestNames);
  do iJF = 1 to nrow(JFNO_ALL);

    IdxJF = JFNO_ALL[iJF];
    &JFSOLUTION = j(nrow(_TYPE_),1,IdxJF);

    RXY = RXY_ALL[iJF,];
    XCORR = (RXX//RXY)||(t(RXY)//1);
    XDATA = XMEAN//XSTD//XN//XCORR;

    %do i=1 %to &&MNTESTS;
      &&MTESTNAME&i = XDATA[,&i];
    %end;

    append;

  end; /* ENDOF: do iJF = 1 to nrow(JFNO_ALL) */

  close &CORRDATA;

  quit;
run;

%if &CONSTRAINT=NONE %then %do;
  %let MODELOPTION=NOINT;
  %let KEEPOTHER=;
%end;
%else %do;
  %let MODELOPTION=NOINT SELECTION=RSQUARE B;
  %let KEEPOTHER=_RSQ_ _P_;
%end;

proc reg data=&CORRDATA
         outest=&BETADATA (keep=&JFSOLUTION &TESTNAMES &KEEPOTHER)
         NOPRINT;
  model SQT = &TESTNAMES / &MODELOPTION;
  by &JFSOLUTION;
  quit;
run;

/*******************************************************************
 Zeidner-Johnson-Vladimirsky Non-negative Beta Weights APproach
*******************************************************************/
%if &CONSTRAINT=POSITIVE1 %then %do;
  proc sort data=&BETADATA;
    by &JFSOLUTION descending _P_ descending _RSQ_;
  run;

  /* Oragnize all possible solutions using two data sets:                */
  /* TmpBetaPositive: solutions with non-negative weights                */
  /* TmpBetaMax: solutions with maximum R for each JF & no. subtests pair */
  data TmpBetaPositive
```

```
      TmpBetaMax
        (keep=&JFSOLUTION _RSQ_ _P_);
    array Beta {&MNTESTS_ASVAB} &TESTNAMES;
    set &BETADATA;
    by &JFSOLUTION descending _P_ descending _RSQ_;
    NegativeWgtFlag = 0;
    do i=1 to &MNTESTS_ASVAB;
      if (Beta{i}=.) then Beta{i} = 0;
      NegativeWgtFlag = NegativeWgtFlag or (Beta{i}<0);
    end;
    /* output all solutions without negative weights */
    if (^NegativeWgtFlag) then
      output TmpBetaPositive;
    /* output subset with maximum R overall for given number of subtests */
    if (First._P_ and ^First.&JFSOLUTION) then do;
      _P_ = _P_+1;
      output TmpBetaMax;
      end;
  run;

  /* output positive weighted solutions with R2 >= max R2 in the next level
*/
  data TmpCompare;
    keep &JFSOLUTION &TESTNAMES _RSQ_;
    merge TmpBetaPositive TmpBetaMax (rename=(_RSQ_=Rmax));
    by &JFSOLUTION descending _P_;
    if(_RSQ_ >= Rmax) then output;
  run;

  /* output only weights with maximum number of subsets for job family */
  data &BETADATA;
    set TmpCompare;
    by &JFSOLUTION descending _RSQ_;
    if First.&JFSOLUTION then output;
  run;
%end;

/*****************************************************************
 HumRRO Simple Non-negative Beta Weights Approach:
 - Entirely ignore solutions with negative weights.
*****************************************************************/
%if &CONSTRAINT=POSITIVE2 %then %do;
  /* keep only solutions with all positive weights */
  data TmpBetaPositive;
    array Beta {&MNTESTS_ASVAB} &TESTNAMES;
    set &BETADATA;
    do i=1 to &MNTESTS_ASVAB;
      if (Beta{i}=.) then Beta{i} = 0;
      else if (Beta{i}<0) then delete;
    end;
  run;

  proc sort data=TmpBetaPositive;
    by &JFSOLUTION descending _RSQ_;
  run;
```

```
  /* output all positive weights solution with maximum R2 */
  data &BETADATA;
    keep &JFSOLUTION &TESTNAMES _RSQ_;
    set TmpBetaPositive;
    by &JFSOLUTION descending _RSQ_;
    if First.&JFSOLUTION then output;
  run;
%end;

%mend;
```

```
/*****************************************************************************

Computing Beta Weights by job family.

*** REQUIRED IN SIMULATION ***

*****************************************************************************/

%macro UKWeights(UKDATA,COVDATA,POPDATA,BETADATA,JFNUM,TYPE);

/* variable names for ASVAB subtests, excluding NO and CS */
%let TESTNAMES=GS AR AS MK MC EI VE;

proc iml;

  Subtest = {&TESTNAMES};

  /* predictor correlation matrix for Army Input Population*/
  use &COVDATA;
  read all var{&TESTNAMES} where(names?Subtest) into CovMat;
  close &COVDATA;

  use &POPDATA;
  read all var{SD} where(test?Subtest) into SDvec;
  %if &TYPE=TIER1 %then %do;
    read all var{MEAN} where(test?Subtest) into Means;
  %end;
  close &POPDATA;

  SDProd = 1/(SDvec#SDvec);
  R = CovMat#SDProd`;

  /*reading in all JFs into JFNO_ALL*/
  use &BETADATA;
  read all var{&JFNUM} into JFNO_ALL;
  NumJF = nrow(JFNO_ALL);

  /*creating SAS dataset containing u weights and k values for all JFs */
  create &UKDATA var{JFNO &TESTNAMES k};

  do idxJF=1 to NumJF;

    /*converting beta weights to b-weights for MOS-level*/

    setin &BETADATA;
    read all var{&TESTNAMES} where(&JFNUM=idxJF) into ObsBeta;

    bweights = ObsBeta#(1/SDvec`);

    /*transform b-weights to u and k values for Tier2 */
    %if &TYPE=TIER2 %then %do;
        /* composite multiplier*/
        CM = 20/(10*(SQRT(bweights*R*bweights`)));
        /* calculate U and K values */
        Uvec = diag(CM)*bweights;
        K = (SUM(Uvec)*50)-100;
```

```
    %end;

    /*transform b-weights to u and k values for Tier1 */
    %else %if &TYPE=TIER1 %then %do;
        /* calculate U and K values */
        Uvec = bweights;
        /* sum ASVAB means weighted by their respective b-weight*/
        K = SUM(Uvec#Means`);
    %end;

    /*merging u values with k value and adding a column for JFNO*/
    UKvec = J(nrow(K),1,idxJF) || Uvec || K;

    append from UKvec;

  end;

  close &UKDATA;
  close &BETADATA;

quit;
run;

%mend;
```

```
/***************************************************************************

Compute criterion scores for individuals in sample &CrossSample

Note: TYPE=ASSIGN prepare cost data in preparation for optimal classification
      using PROC TRANS.

*** REQUIRED IN SIMULATION ***

***************************************************************************/

%macro
ComputeCriterionScores(CriterionData,CrossSample,JFWgtData,JFSOLN,TYPE);

%if &TYPE=ASSIGN %then %do;
  proc sort data=kfvlib.entryMOS150 out=tmp;
    by &JFSOLN;
  run;
  proc means data=tmp noprint;
    var allocKFV;
    by &JFSOLN;
    output out=AllocData sum=;
  run;
%end;

proc iml;
  use &JFWgtData;
  read all var{K GS AR AS MK MC EI VE} into WgtMat;
  close &JFWgtData;

  use &CrossSample;
  read all var {GS AR AS MK MC EI VE} into X;
  close &CrossSample;
  X = repeat(-1,nrow(X),1) || X;

  Y = X*t(WgtMat);

  create &CriterionData var("JF1":"&JFSOLN");

  %if &TYPE=ASSIGN %then %do;
    use AllocData;
    read all var{allocKFV} into tmpvec;
    tmpvec = t(tmpvec);
    append from tmpvec;
    close AllocData;
  %end;

  append from Y;
  close &CriterionData;

quit;
run;

%mend;
```

```
/*****************************************************************************

Optimally assign persons to JFSOLN jobs. The program then compute their
predicted performance in their respective optimal jobs.

*** REQUIRED IN SIMULATION ***

*****************************************************************************/

%macro OptimalAssignmentPredictedScores(OPJMData,EvalData,AssignData,JFSOLN);

data TmpAssign;
  set &AssignData;
  if _n_>1 then do;
    person = 'P' || put(_n_-1,z4.);
    supply = 1;
  end;
run;

proc trans cost=TmpAssign out=AssignSolution maximum;
  tailnode person;
  headnode JF1-&JFSOLN;
  supply supply;
run;

data tmp;
  array AJF150{150} JF1-JF150; /* not all 150 use all the time */
  set AssignSolution end=last;
  if _n_>1 and ^last;
  do &JFSOLN=1 to 150 until (AJF150{&JFSOLN}>0);end;
  randToSort = uniform(8000+&IREP);
  keep person &JFSOLN randToSort;
run;
proc sort data=tmp;
  by &JFSOLN randToSort;
run;
proc sort data=kfvlib.entryMOS150 out=tmp2;
  by &JFSOLN;
run;
data tmp2;
  set tmp2;
  do i=1 to allocKFV;
    output;
  end;
  keep &JFSOLN MOS150;
run;
data MOS150assignIdx;
  merge tmp tmp2;
  by &JFSOLN;
  keep MOS150 &JFSOLN person;
run;
proc sort data=MOS150assignIdx;
  by person;
run;

proc iml;
```

```
  use &EvalData;
  read all var("JF1":"JF150") into matY;
  close &EvalData;

  use MOS150assignIdx;
  read all var{MOS150} into MOS150idx;
  read all var{&JFSOLN} into JFSOLNidx;
  close MOS150assignIdx;

  assignN = nrow(matY);
  optY = repeat(0,assignN,1);
  do i=1 to assignN;
    optY[i] = matY[i,MOS150idx[i]];
  end;

  outMat =
repeat(&IREP,assignN,1)||repeat(&IREPC,assignN,1)||MOS150idx||JFSOLNidx||optY
;
  create &OPJMData var{REP REPC MOS150 &JFSOLN YPP};
  append from outMat;
  close &OPJMData;

quit;
run;

%mend;
```

```
/****************************************************************************

Program implenting the K-Fold validation of JZ procedure

****************************************************************************/

%macro KFoldEvalMPP(KFVOPJMDATA,RANDSEEDBASE,JFSOLN,BCONSTRAINT,UTIER,
REPSTART,REPEND);

/* Currently number of sample C partitions is fixed */
%let NUMREPC=5;

%do IREP=&REPSTART %to &REPEND;

  %let REPSEED=%eval(&RANDSEEDBASE+&IREP);

  /* Partition data in samples A+B+C1+C2+...+C&NUMREPC */
  %CreateSampleABC(&IREP,&REPSEED,&NUMREPC);

  /* Using sample A, compute weights for evaluation of MPP -- always based on
JF150 */

    * Compute descriptive stats;
    %ComputeDescriptives(SampleDataA,descripA,corrA,covA,covRefpopA);

    * Step 1 - correct MOS validity for criterion unreliability and
restriction in range;
    %CorrectUnreliability(corXYA,corCVA,descripA,corrA,kfvLib.entrymos155);
    * note: range restriction correction relative to Army - covRefpopA
computed from input data;
    %CorrectRangeRestriction(validityA,covRefpopA,covA,corCVA);
    * Step 2 - compute JF validities -- corrected to Army input population;
    %JFValid(JF150validityA,validityA,JF150,kfvLib.entrymos155);
    * Step 3 - compute beta weights -- CONSTRAINT=NONE for evaluation sample
A ;
    %BetaWeights(JF150BetaA,covRefpopA,JF150validityA,JF150,NONE);
    * Step 4&5 -- final JF150 evaluation weights for computing MPP -- note
param TIER1 ;

%UKWeights(JF150ukA,covRefpopA,kfvLib.PopDescripArmy,JF150BetaA,JF150,TIER1);

  /* Using sample B, compute assignment weights based on solution &JFSOLN */
    * Compute descriptive stats;
    %ComputeDescriptives(SampleDataB,descripB,corrB,covB,covRefpopB);
    * Step 1 - correct MOS validity for criterion unreliability and
restriction in range;
    %CorrectUnreliability(corXYB,corCVB,descripB,corrB,kfvLib.entrymos155);
    * note: range restriction correction relative to Army - covRefpopA
computed from input data;
    %CorrectRangeRestriction(validityB,covRefpopB,covB,corCVB);
    * Step 2 - compute &JFSOLN JF validities -- corrected to Army input
population;
    %JFValid(JFSOLNvalidityB,validityB,&JFSOLN,kfvLib.entrymos155);
    * Step 3 - compute &JFSOLN beta weights -- CONSTRAINT=NONE for evaluation
sample A ;
```

```
%BetaWeights(JFSOLNBetaB,covRefpopB,JFSOLNvalidityB,&JFSOLN,&BCONSTRAINT);
    * Step 4&5 -- final &JFSOLN assignment weights -- note param NOT TIER2
(NOT want visible tier) ;

%UKWeights(JFSOLNukB,covRefpopB,kfvLib.PopDescripArmy,JFSOLNBetaB,&JFSOLN,&UT
IER);

  /* Using sample C subsets */
    %do IREPC=1 %to &NUMREPC;
      * Compute prediction/eval criterion scores using sampleA MOS150 LSE
wgts (JF150ukA) ;

%ComputeCriterionScores(CrossDataEval,SampleDataC&IREPC,JF150ukA,JF150,EVAL);
      * Compute analysis/assignment criterion scores using sampleB JF
solution wgt ;

%ComputeCriterionScores(CrossDataAssign,SampleDataC&IREPC,JFSOLNukB,&JFSOLN,A
SSIGN);
      * Run optimal assignment;

%OptimalAssignmentPredictedScores(RepOPJMdata,CrossDataEval,CrossDataAssign,&
JFSOLN);
      * Append OPJM data ;
      proc append base=&KFVOPJMDATA data=RepOPJMdata;
      run;
    %end;

%end;

%mend;

/*
%let TMPJF=JF9;
proc datasets; delete TmpMpp&TMPJF;run;
%KFoldEvalMPP(TmpMpp&TMPJF,1001,&TMPJF,POSITIVE1,TIER2,1,1);
proc means data=TmpMpp&TMPJF;
  var YPP;
*  class REPC;
run;

%let TMPJF=JF17;
proc datasets; delete TmpMpp&TMPJF;run;
%KFoldEvalMPP(TmpMpp&TMPJF,49,1001,&TMPJF,POSITIVE1,TIER2,1,1);
proc means data=TmpMpp&TMPJF;
  var YPP;
run;

%let TMPJF=JF150;
proc datasets; delete TmpMpp&TMPJF;run;
%KFoldEvalMPP(TmpMpp&TMPJF,49,1001,&TMPJF,POSITIVE1,TIER2,1,1);
proc means data=TmpMpp&TMPJF;
  var YPP;
run;

*/
```

```
/*****************************************************************************

Calculate overall MPP by replication across conditions:
  NUM_JF, BETA_CONSTRAINT, TIER(a.k.a. EQUAL VARIANCE)

*****************************************************************************/

options formchar='|-++++++' nodate nonumber;

/* *** EDIT AS NEEDED *** Output data library */
libname mppsim "D:\NEW AA\SAS Workspace\KFVPGMDISTN\MmmSimData";

data ypp/view=ypp;
  set
    mppsim.ypp_jf9_none_tier1_1_49      (in=in_jf9_none_tier1)
    mppsim.ypp_jf9_none_tier2_1_49      (in=in_jf9_none_tier2)
    mppsim.ypp_jf9_positive1_tier1_1_49 (in=in_jf9_positive1_tier1)
    mppsim.ypp_jf9_positive1_tier2_1_49 (in=in_jf9_positive1_tier2)
    mppsim.ypp_jf9_positive2_tier1_1_49 (in=in_jf9_positive2_tier1)
    mppsim.ypp_jf9_positive2_tier2_1_49 (in=in_jf9_positive2_tier2)
    mppsim.ypp_jf17_none_tier1_1_49     (in=in_jf17_none_tier1)
    mppsim.ypp_jf17_none_tier2_1_49     (in=in_jf17_none_tier2)
    mppsim.ypp_jf17_positive1_tier1_1_49(in=in_jf17_positive1_tier1)
    mppsim.ypp_jf17_positive1_tier2_1_49(in=in_jf17_positive1_tier2)
    mppsim.ypp_jf17_positive2_tier1_1_49(in=in_jf17_positive2_tier1)
    mppsim.ypp_jf17_positive2_tier2_1_49(in=in_jf17_positive2_tier2)
    ;
    if in_jf9_none_tier1 then do;
      num_jf=9; beta_constraint=0; tier=1; end;
    else if in_jf9_none_tier2 then do;
      num_jf=9; beta_constraint=0; tier=2; end;
    else if in_jf9_positive1_tier1 then do;
      num_jf=9; beta_constraint=1; tier=1; end;
    else if in_jf9_positive1_tier2 then do;
      num_jf=9; beta_constraint=1; tier=2; end;
    else if in_jf9_positive2_tier1 then do;
      num_jf=9; beta_constraint=2; tier=1; end;
    else if in_jf9_positive2_tier2 then do;
      num_jf=9; beta_constraint=2; tier=2; end;
    else if in_jf17_none_tier1 then do;
      num_jf=17; beta_constraint=0; tier=1; end;
    else if in_jf17_none_tier2 then do;
      num_jf=17; beta_constraint=0; tier=2; end;
    else if in_jf17_positive1_tier1 then do;
      num_jf=17; beta_constraint=1; tier=1; end;
    else if in_jf17_positive1_tier2 then do;
      num_jf=17; beta_constraint=1; tier=2; end;
    else if in_jf17_positive2_tier1 then do;
      num_jf=17; beta_constraint=2; tier=1; end;
    else if in_jf17_positive2_tier2 then do;
      num_jf=17; beta_constraint=2; tier=2; end;
run;

proc means data=ypp noprint;
  by num_jf beta_constraint tier rep repc;
  var ypp;
```

```
  output out=mpp_overall; run;
data mppsim.mpp_overall;
  set mpp_overall;
  if _stat_='MEAN';
  drop _type_ _freq_ _stat_;
  rename ypp=mpp;
run;
```

APPENDIX D: PLOTTING OF MEAN MPP AND STANDARD ERROR BY MOS

Figure 1
MPP and Standard Error by MOS and Job Family Configuration for CL, CO, and EL Job Families Using Unstandardized Test Composites

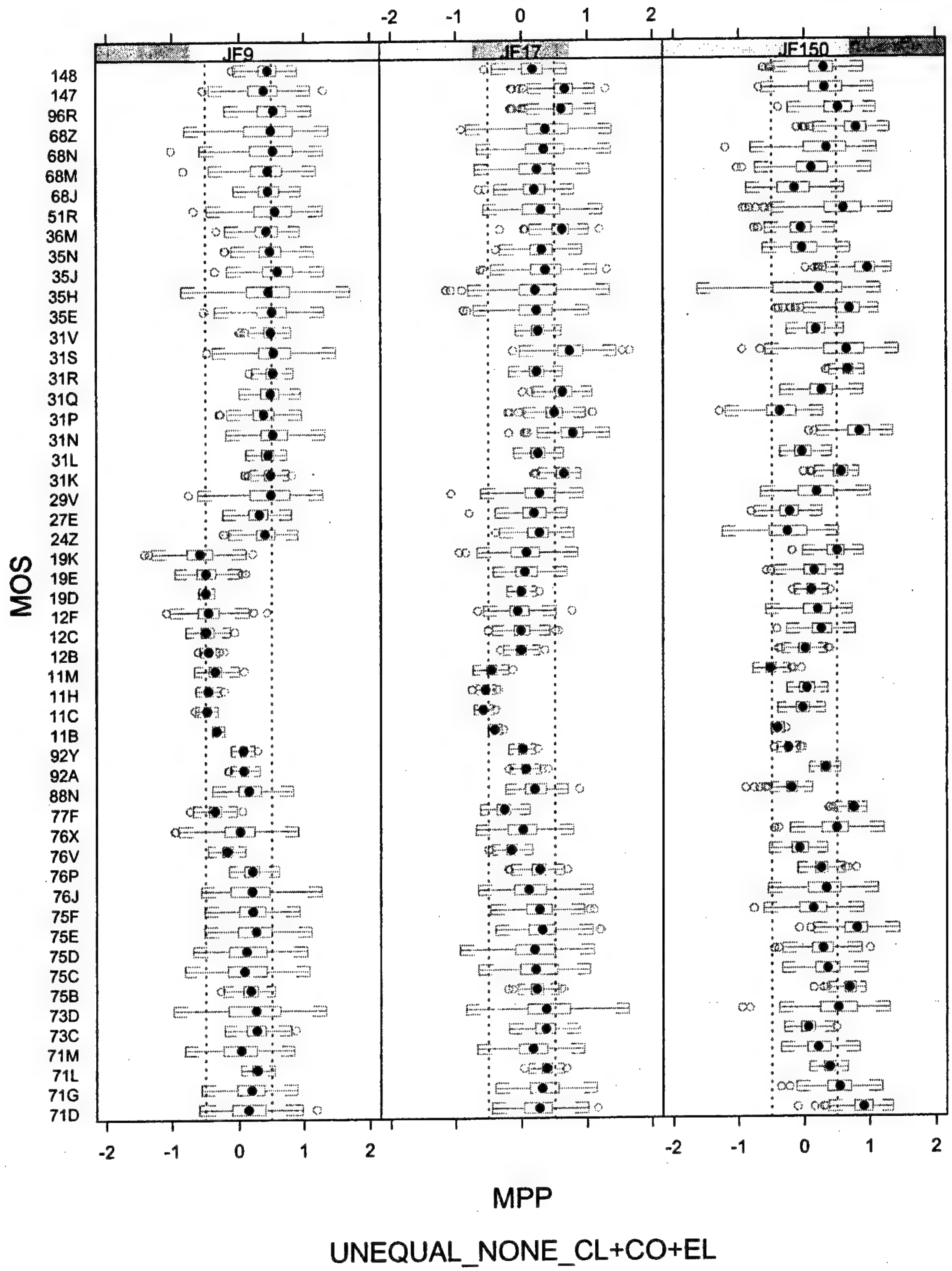


Figure 2

MPP and Standard Error by MOS and Job Family Configuration for FA, GM, and MM Job Families Using Unstandardized Test Composites

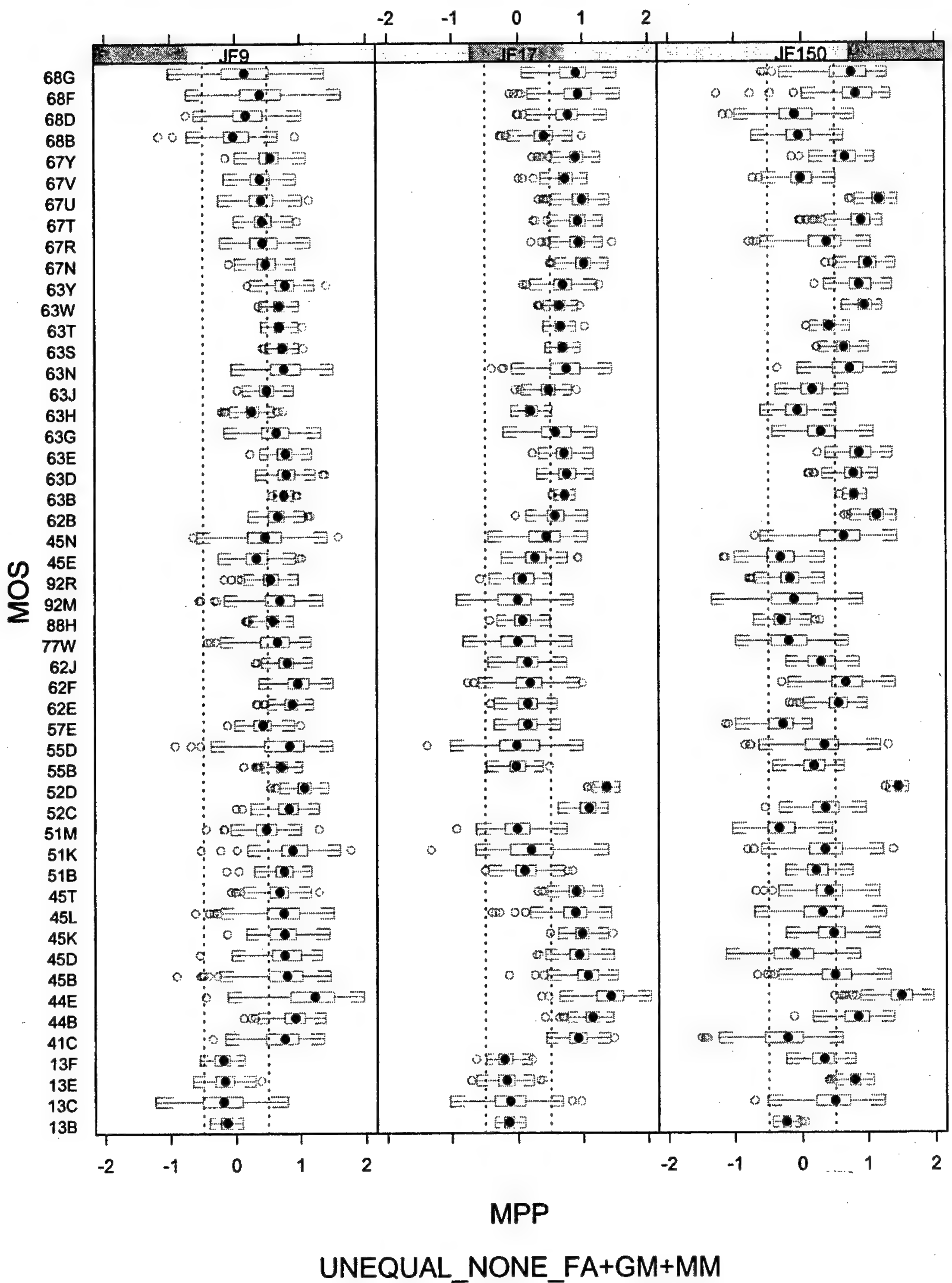


Figure 3
MPP and Standard Error by MOS and Job Family Configuration for OF, SC, and ST Job Families Using Unstandardized Test Composites

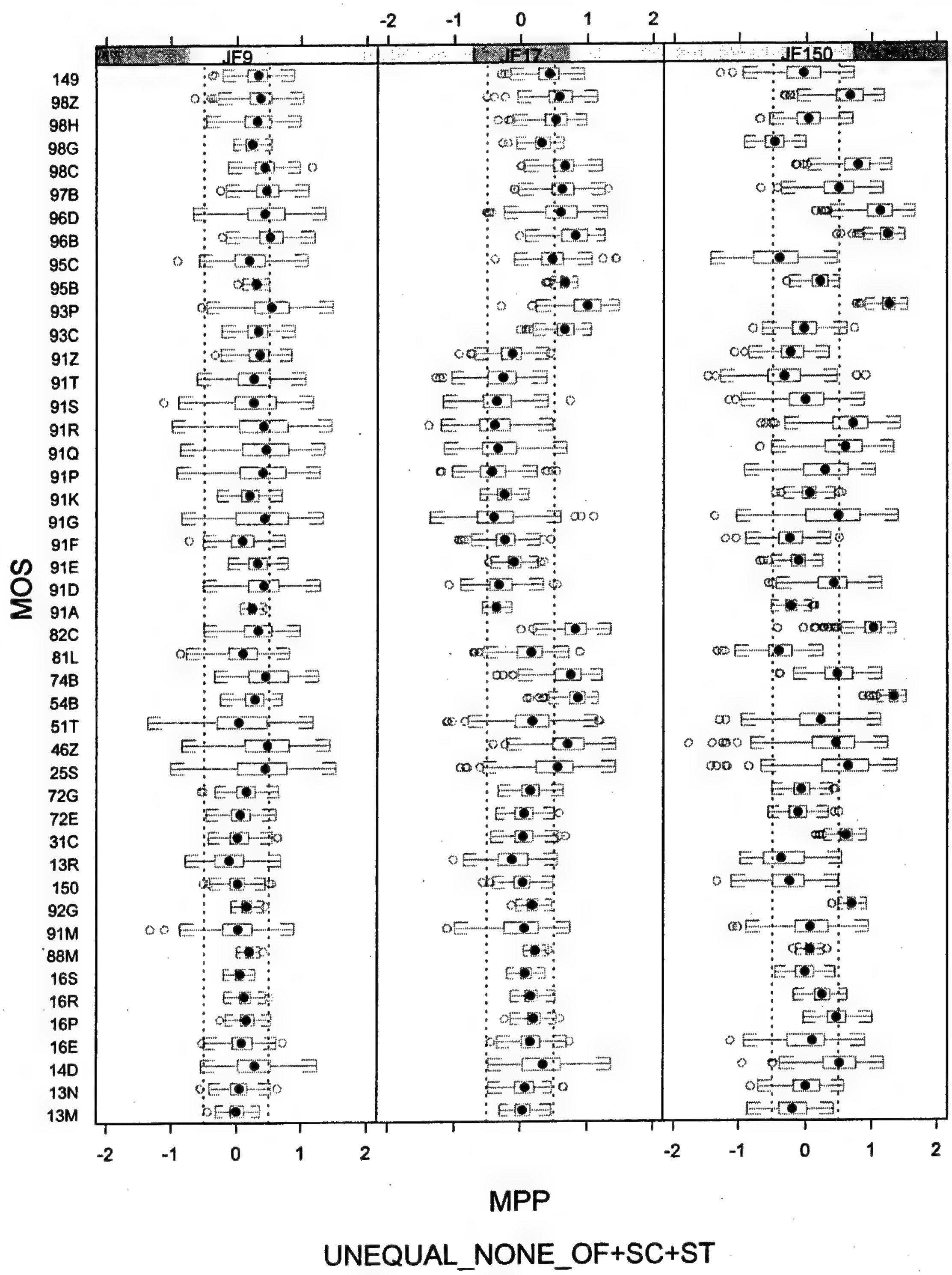


Figure 4

MPP and Standard Error by MOS and Job Family Configuration for CL, CO, and EL Job Families Using Standardized Test Composites

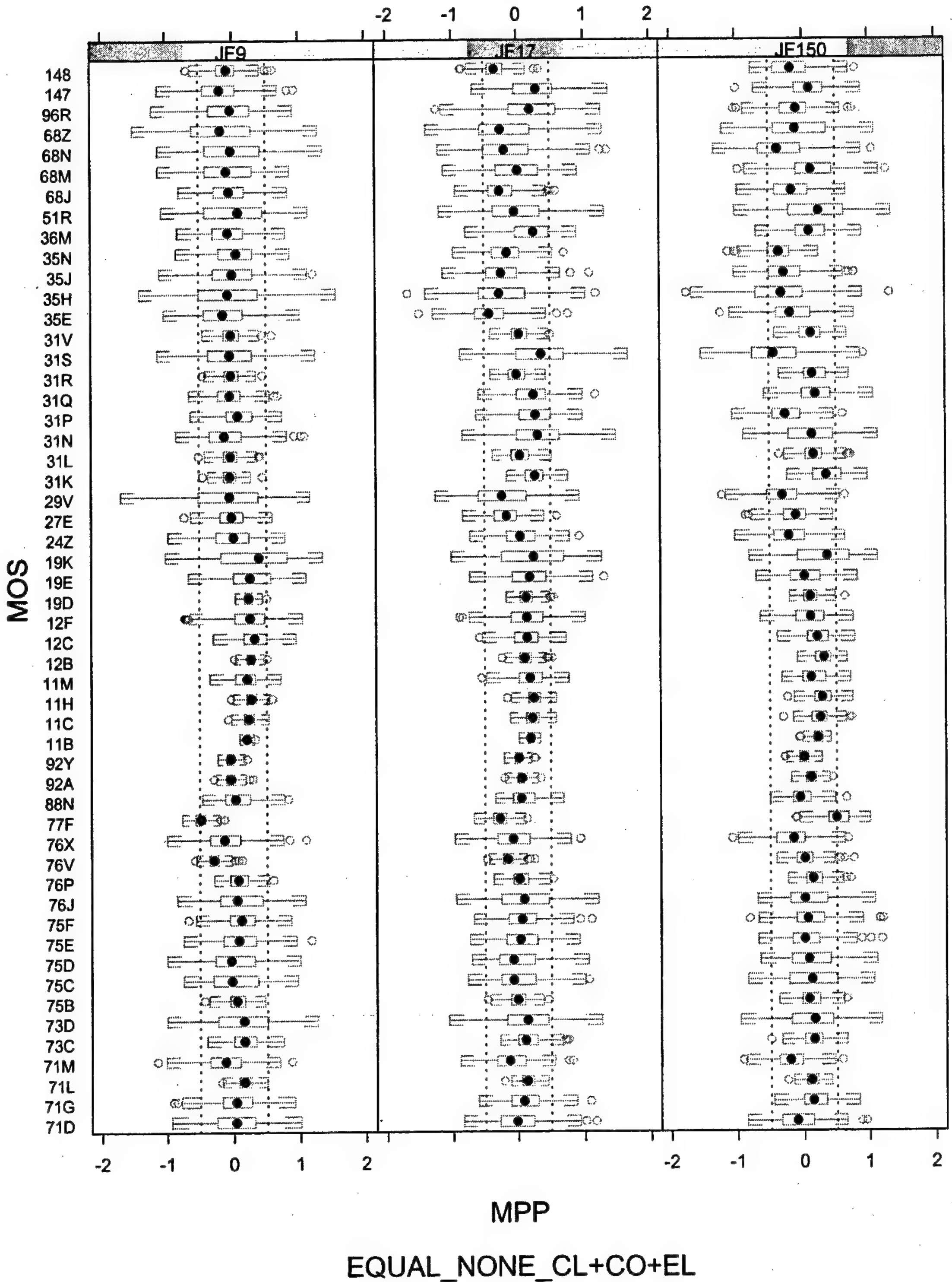


Figure 5

MPP and Standard Error by MOS and Job Family Configuration for FA, GM, and MM Job Families Using Standardized Test Composites

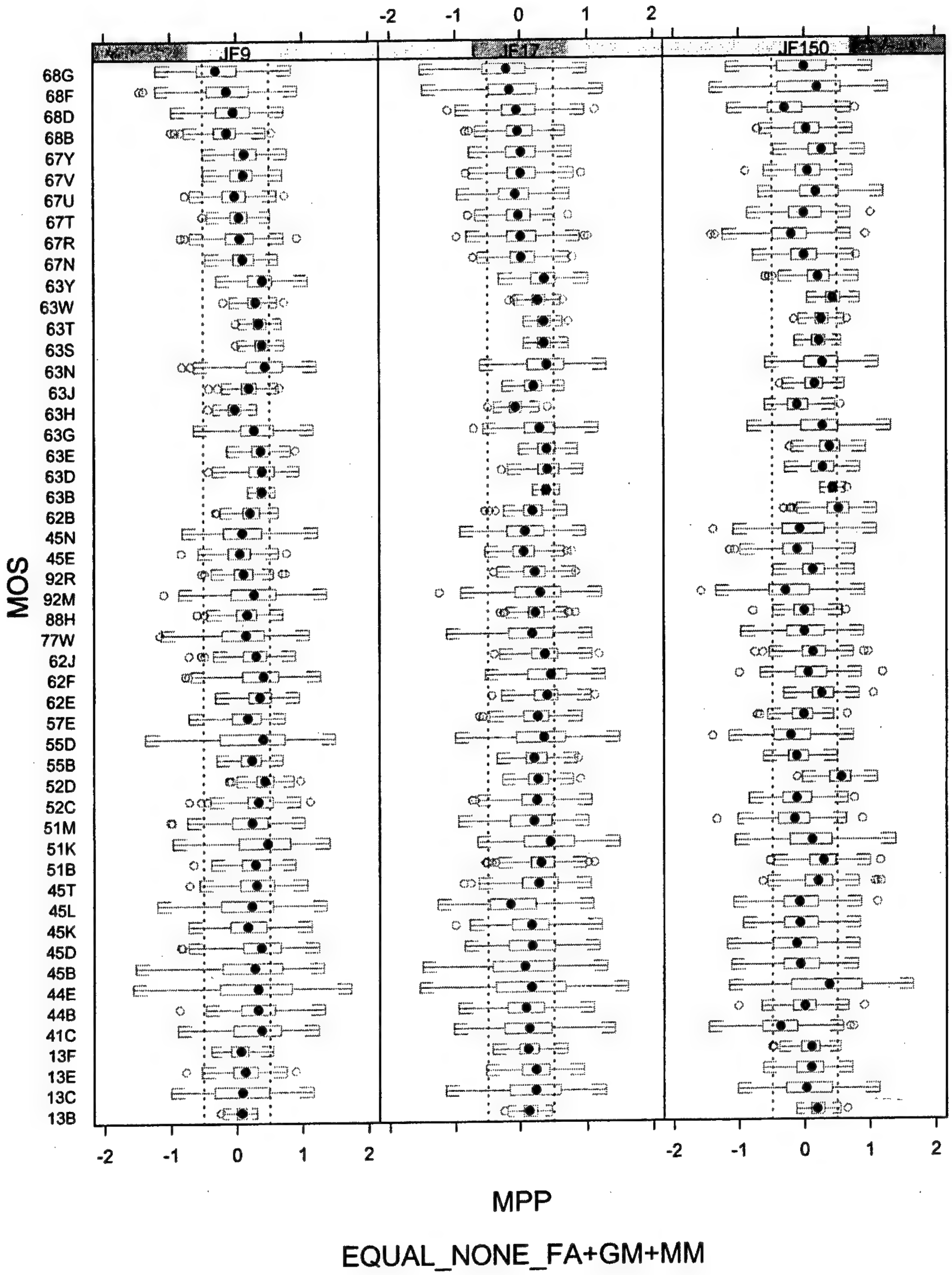
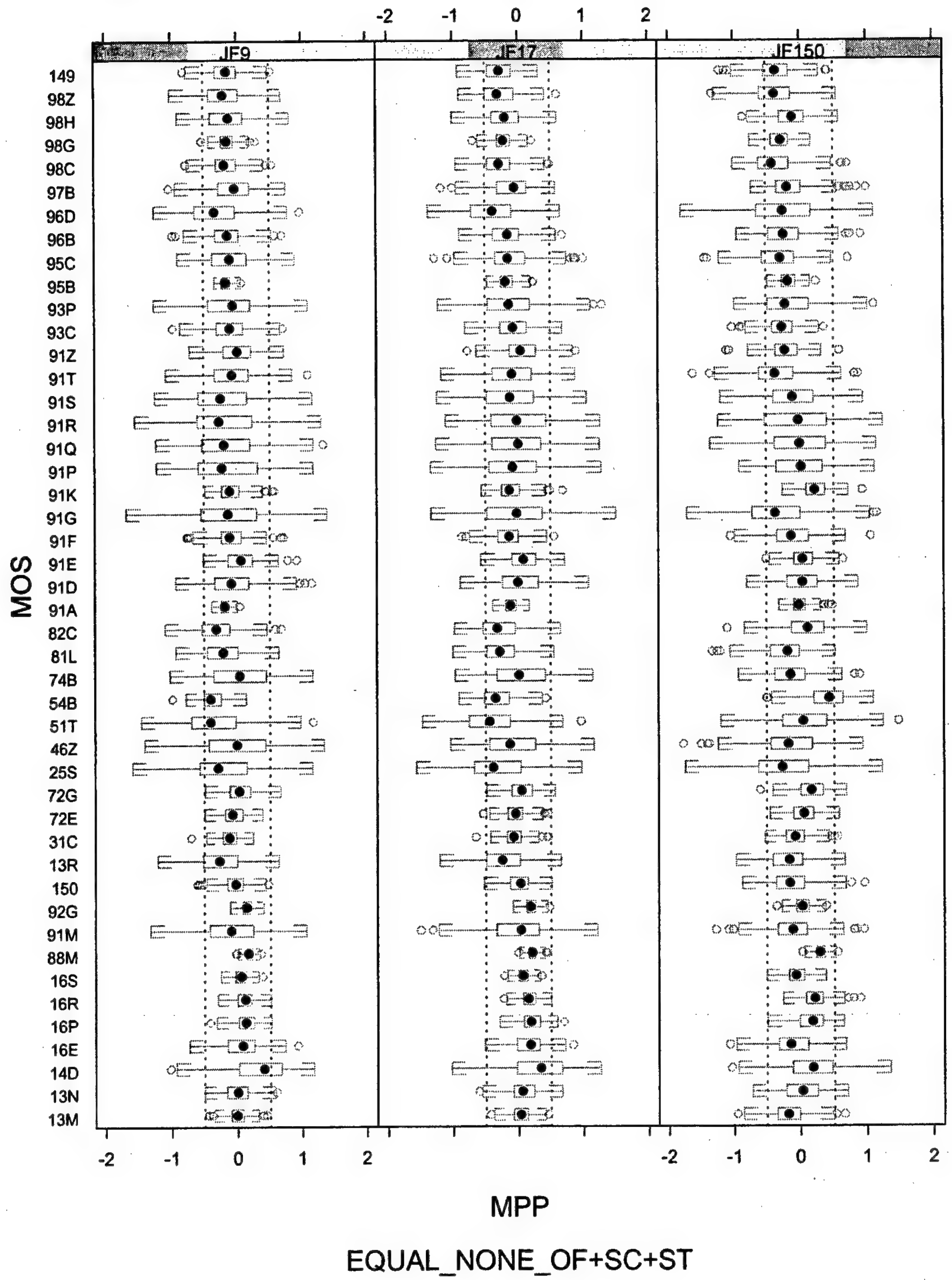


Figure 6
MPP and Standard Error by MOS and Job Family Configuration for OF, SC, and ST Job Families Using Standardized Test Composites



APPENDIX E: MEAN MPP AND STANDARD ERROR BY MOS

Table 1
Mean MPP and Standard Error by MOS and Job Family Configuration Using Unstandardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
1	-0.3297	0.0393	-0.4058	0.0403	-0.4144	0.0396
2	-0.4746	0.0688	-0.5741	0.0622	-0.0269	0.1436
3	-0.4510	0.0704	-0.5479	0.0625	0.0433	0.1425
4	-0.3512	0.1313	-0.4513	0.1081	-0.5072	0.1188
5	-0.4456	0.0619	-0.0021	0.1082	0.0068	0.1390
6	-0.4704	0.1344	0.0051	0.1925	0.2718	0.2074
7	-0.4556	0.2633	-0.0463	0.2350	0.1825	0.2876
8	-0.1445	0.1186	-0.1415	0.1017	-0.2375	0.0813
9	-0.1831	0.4007	-0.1281	0.3687	0.4469	0.3883
10	-0.1736	0.2025	-0.1855	0.1883	0.7865	0.1258
11	-0.2128	0.1520	-0.2063	0.1379	0.3150	0.2186
12	0.0123	0.1389	0.0391	0.1454	-0.1940	0.2735
13	0.0380	0.1800	0.0741	0.1919	0.0113	0.2650
14	-0.1195	0.2889	-0.1167	0.2930	-0.3314	0.3660
15	0.3002	0.3634	0.3326	0.3944	0.4838	0.3600
16	0.0825	0.2264	0.1410	0.2078	0.0078	0.3993
17	0.1651	0.1445	0.2012	0.1439	0.4694	0.2095
18	0.1306	0.1181	0.1647	0.1301	0.2463	0.1577
19	0.0549	0.0919	0.0840	0.1000	-0.0011	0.1873
20	-0.4915	0.0533	0.0054	0.0969	0.1133	0.1190
21	-0.4824	0.2015	0.0704	0.2204	0.1417	0.2352
22	-0.5818	0.3035	0.0465	0.3412	0.4829	0.2026
23	0.3981	0.2120	0.2349	0.2400	-0.2504	0.3626
24	0.3878	0.5078	0.4778	0.4459	0.5613	0.5241
25	0.3067	0.2012	0.1795	0.2376	-0.2318	0.2239
26	0.4595	0.4002	0.2685	0.3460	0.1748	0.3650
27	0.0484	0.2164	0.0522	0.1981	0.6086	0.1467
28	0.4725	0.1368	0.6098	0.1506	0.5491	0.1615
29	0.4311	0.1285	0.2465	0.1536	-0.0128	0.1737
30	0.5357	0.2962	0.7513	0.2586	0.8172	0.2517
31	0.3710	0.2233	0.4850	0.2141	-0.3702	0.3323
32	0.4698	0.2008	0.6188	0.1895	0.2690	0.2550
33	0.5067	0.1213	0.2307	0.1656	0.6635	0.1151
34	0.5398	0.3644	0.7191	0.3164	0.5718	0.4705
35	0.4713	0.1450	0.2498	0.1393	0.1861	0.1840
36	0.4907	0.3431	0.1925	0.3700	0.6257	0.2886
37	0.4576	0.4852	0.2377	0.4780	0.0540	0.6860
38	0.5809	0.3335	0.3589	0.3429	0.9124	0.2484

Table 1
Mean MPP and Standard Error by MOS and Job Family Configuration Using Unstandardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
39	0.4754	0.2550	0.2979	0.2541	0.0106	0.2810
40	0.4102	0.2297	0.5805	0.2158	-0.0608	0.2279
41	0.7189	0.3206	0.9237	0.2073	-0.2811	0.4219
42	0.9018	0.2269	1.1328	0.1590	0.8101	0.2528
43	1.1310	0.4813	1.3845	0.3026	1.4615	0.2635
44	0.7315	0.4134	1.0518	0.2447	0.4927	0.3455
45	0.7526	0.3072	0.9239	0.2066	-0.1171	0.4179
46	0.3293	0.2340	0.2704	0.2294	-0.3212	0.2874
47	0.7378	0.2701	0.9841	0.1467	0.4478	0.2775
48	0.6939	0.3889	0.8441	0.3048	0.3059	0.4134
49	0.4681	0.3964	0.4033	0.3334	0.5696	0.4319
50	0.6521	0.2288	0.8877	0.1738	0.4007	0.3043
51	0.4548	0.4698	0.6803	0.3510	0.3726	0.5102
52	0.7415	0.2023	0.1083	0.2288	0.2259	0.2064
53	0.8759	0.3129	0.2101	0.4167	0.3375	0.4000
54	0.4821	0.2374	-0.0076	0.2819	-0.3248	0.2910
55	0.5149	0.4060	0.3019	0.3847	0.5404	0.4468
56	0.0551	0.4980	0.1518	0.4269	0.1946	0.4501
57	0.8038	0.2215	1.0725	0.1498	0.3470	0.2967
58	1.0539	0.1481	1.3502	0.0859	1.4473	0.0650
59	0.2701	0.1896	0.8224	0.1972	1.3187	0.1050
60	0.7089	0.1441	-0.0200	0.1768	0.1775	0.2126
61	0.7405	0.4227	0.0067	0.4361	0.2885	0.3997
62	0.4123	0.1895	0.1474	0.2082	-0.3106	0.2464
63	0.6409	0.1832	0.5703	0.1897	1.1173	0.1485
64	0.8539	0.1495	0.1467	0.2050	0.5313	0.2271
65	0.9489	0.2387	0.1628	0.3178	0.6533	0.3288
66	0.7902	0.1621	0.1430	0.2335	0.2925	0.2684
67	0.7550	0.0700	0.7198	0.0695	0.7930	0.0791
68	0.7896	0.1933	0.7557	0.1881	0.7658	0.1931
69	0.7714	0.1581	0.7153	0.1608	0.8830	0.2109
70	0.6244	0.2869	0.5808	0.2999	0.2984	0.3052
71	0.2647	0.1550	0.2008	0.1347	-0.0659	0.2397
72	0.4945	0.1524	0.4617	0.1609	0.1541	0.2307
73	0.7614	0.3194	0.7194	0.3204	0.6957	0.3291
74	0.7359	0.1094	0.6955	0.1060	0.6346	0.1437
75	0.6921	0.1084	0.6537	0.1037	0.4231	0.1190
76	0.6842	0.1176	0.6505	0.1184	0.9576	0.1251

Table 1
Mean MPP and Standard Error by MOS and Job Family Configuration Using Unstandardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
77	0.7719	0.2098	0.7042	0.2038	0.8840	0.2185
78	0.4775	0.2007	1.0105	0.1675	0.9972	0.1881
79	0.4428	0.2865	0.9183	0.1837	0.3313	0.3606
80	0.4325	0.1888	0.9186	0.1829	0.8670	0.2447
81	0.4152	0.2573	0.9662	0.2020	1.1654	0.1274
82	0.3934	0.2163	0.7360	0.1628	-0.0083	0.2246
83	0.5319	0.2118	0.8913	0.1697	0.6592	0.2174
84	0.0084	0.3041	0.3979	0.2234	-0.0488	0.2743
85	0.1956	0.3420	0.7613	0.2428	-0.0907	0.3588
86	0.3956	0.4638	0.9097	0.3196	0.8181	0.3439
87	0.1780	0.5084	0.8672	0.3052	0.7000	0.3786
88	0.4513	0.2205	0.1843	0.2521	-0.1457	0.3318
89	0.4175	0.3315	0.2164	0.3394	0.1113	0.3735
90	0.4961	0.4279	0.3315	0.4287	0.2973	0.4564
91	0.4401	0.5062	0.3622	0.4708	0.7686	0.2700
92	0.1623	0.3303	0.2665	0.3133	0.8874	0.2164
93	0.1836	0.2855	0.3350	0.3010	0.5318	0.2927
94	0.2805	0.1104	0.3795	0.1109	0.3830	0.1111
95	0.0223	0.3239	0.1592	0.2922	0.2179	0.2389
96	0.0687	0.2124	0.0609	0.1822	-0.1148	0.1895
97	0.1409	0.2111	0.1442	0.1916	-0.0605	0.1844
98	0.2714	0.2105	0.3533	0.2055	0.0636	0.1459
99	0.2614	0.4901	0.3942	0.4377	0.4817	0.4024
100	0.4806	0.3771	0.6982	0.2950	0.4783	0.3105
101	0.1716	0.1542	0.2299	0.1372	0.6890	0.1264
102	0.1562	0.4031	0.2399	0.3809	0.3552	0.2631
103	0.1358	0.3841	0.2082	0.4049	0.2774	0.2545
104	0.2584	0.3426	0.3236	0.3089	0.7747	0.2510
105	0.2070	0.2737	0.2698	0.2709	0.1248	0.2995
106	0.2000	0.3939	0.1353	0.3502	0.3140	0.3161
107	0.1966	0.1631	0.2565	0.1661	0.2699	0.1453
108	-0.1705	0.1086	-0.1498	0.1130	-0.0697	0.1705
109	0.0057	0.3460	0.0031	0.3026	0.4686	0.2978
110	-0.3623	0.1272	-0.2676	0.1440	0.7465	0.1099
111	0.5933	0.3269	-0.0039	0.3360	-0.1909	0.3542
112	0.0707	0.3171	0.1246	0.2870	-0.4060	0.2849
113	0.3225	0.3011	0.8078	0.2338	0.9784	0.2584
114	0.5673	0.1471	0.0624	0.1679	-0.2834	0.1847

Table 1
Mean MPP and Standard Error by MOS and Job Family Configuration Using Unstandardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
115	0.1932	0.0739	0.2216	0.0747	0.0577	0.0926
116	0.1715	0.2335	0.2084	0.2113	-0.2086	0.1497
117	0.2349	0.0791	-0.3548	0.0848	-0.2189	0.1145
118	0.4138	0.3338	-0.3018	0.2568	0.3733	0.3447
119	0.3243	0.1891	-0.0870	0.1538	-0.1271	0.1737
120	0.0861	0.2479	-0.2330	0.2168	-0.2502	0.2850
121	0.3865	0.4985	-0.3716	0.4199	0.3974	0.5774
122	0.1947	0.1904	-0.2337	0.1466	0.0424	0.1595
123	0.0086	0.3536	0.0143	0.3685	0.0644	0.3640
124	0.3705	0.4708	-0.4123	0.3144	0.2632	0.4409
125	0.4141	0.4829	-0.3189	0.3639	0.5441	0.4066
126	0.3910	0.4796	-0.3730	0.3327	0.6318	0.4166
127	0.2639	0.4416	-0.3485	0.3099	-0.0150	0.4025
128	0.2638	0.3543	-0.2772	0.3103	-0.3270	0.3809
129	0.3425	0.2166	-0.1500	0.2120	-0.2217	0.2448
130	0.0799	0.0912	0.0598	0.0972	0.3271	0.1030
131	0.1556	0.1025	0.1893	0.1100	0.6909	0.0891
132	0.6559	0.3341	-0.0329	0.3576	-0.1247	0.4246
133	0.5462	0.1812	0.0778	0.2149	-0.1878	0.2070
134	0.0613	0.0787	0.0129	0.0831	-0.2451	0.0760
135	0.3237	0.2291	0.6426	0.1899	-0.0313	0.2619
136	0.5305	0.3808	0.9674	0.2718	1.2406	0.1460
137	0.3032	0.0938	0.6422	0.0892	0.1868	0.1765
138	0.1932	0.3351	0.4819	0.2730	-0.4357	0.4240
139	0.5205	0.2687	0.7885	0.2616	1.2125	0.1602
140	0.4323	0.3974	0.5747	0.3594	1.0827	0.2970
141	0.5042	0.2816	0.6073	0.2403	0.5102	0.2963
142	0.4622	0.2570	0.6160	0.2579	0.4739	0.3298
143	0.4265	0.2154	0.6289	0.2263	0.7558	0.2853
144	0.2347	0.1221	0.3181	0.1617	-0.4737	0.1833
145	0.3140	0.2848	0.4912	0.2562	0.0384	0.2527
146	0.3494	0.2604	0.5566	0.2644	0.6351	0.3059
147	0.3616	0.3183	0.6407	0.2327	0.3124	0.3541
148	0.4385	0.1973	0.1672	0.2384	0.2474	0.3314
149	0.3093	0.2214	0.4016	0.2246	-0.0614	0.3888
150	0.0084	0.1789	0.0287	0.1763	-0.2595	0.3239

Table 2
Mean MPP and Standard Error by MOS and Job Family Configuration Using Standardized Test Composites

	9		17		150	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**
1	0.2092	0.0442	0.1945	0.0669	0.2214	0.0882
2	0.2419	0.1143	0.2212	0.1381	0.2460	0.1643
3	0.2784	0.1146	0.2553	0.1363	0.2901	0.1856
4	0.1842	0.2131	0.1973	0.2526	0.1635	0.2353
5	0.2662	0.0880	0.1275	0.1407	0.2971	0.1534
6	0.3243	0.2371	0.1427	0.2606	0.2218	0.2290
7	0.2459	0.3620	0.1340	0.3530	0.1004	0.2942
8	0.0675	0.1162	0.1394	0.1404	0.2092	0.1497
9	0.0870	0.5066	0.2123	0.5106	0.0483	0.4739
10	0.1206	0.2835	0.2208	0.3016	0.0742	0.3008
11	0.0567	0.1892	0.1253	0.2116	0.0882	0.2112
12	0.0012	0.1489	0.0290	0.1506	-0.1797	0.2635
13	-0.0024	0.2148	0.0662	0.2363	0.0210	0.3205
14	-0.2571	0.3573	-0.2193	0.3674	-0.1797	0.3124
15	0.3288	0.4683	0.2987	0.4812	0.1646	0.4301
16	0.0663	0.2848	0.1358	0.2707	-0.1289	0.3257
17	0.1346	0.1721	0.1827	0.1830	0.1504	0.2360
18	0.1115	0.1447	0.1530	0.1480	0.2145	0.1862
19	0.0485	0.1089	0.0710	0.1094	-0.0559	0.1885
20	0.2372	0.0844	0.1424	0.1459	0.1079	0.1374
21	0.2741	0.3820	0.1921	0.3631	0.0140	0.2953
22	0.2980	0.5839	0.2179	0.5463	0.3088	0.4735
23	-0.0018	0.3211	0.0392	0.3116	-0.2051	0.3175
24	-0.2103	0.5536	-0.3076	0.5167	-0.2588	0.5413
25	-0.0208	0.2458	-0.1744	0.2530	-0.1285	0.2451
26	-0.0554	0.5928	-0.2233	0.4756	-0.3073	0.3232
27	-0.1202	0.1491	-0.0751	0.1647	-0.0663	0.1963
28	-0.0421	0.1322	0.2574	0.1932	0.3745	0.2837
29	-0.0257	0.1586	0.0408	0.1671	0.1650	0.2086
30	-0.0760	0.3561	0.3236	0.4576	0.1205	0.4384
31	0.0789	0.2732	0.2615	0.3390	-0.2553	0.2918
32	-0.0324	0.2549	0.2465	0.3203	0.2144	0.3174
33	-0.0183	0.1523	-0.0034	0.1653	0.1721	0.2281
34	-0.0390	0.4816	0.3283	0.5138	-0.4029	0.4880
35	-0.0114	0.1740	0.0337	0.1712	0.1215	0.2188
36	-0.1077	0.4520	-0.4117	0.3659	-0.1501	0.3920
37	-0.0583	0.6224	-0.2215	0.5154	-0.3334	0.5577
38	-0.0015	0.4115	-0.2066	0.3714	-0.2417	0.3488

Table 2
Mean MPP and Standard Error by MOS and Job Family Configuration Using Standardized Test Composites

	9		17		150	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**
39	0.0478	0.3503	-0.1530	0.3016	-0.3583	0.2270
40	-0.0559	0.3087	0.2225	0.3529	0.1317	0.3182
41	0.2967	0.4949	0.1272	0.4902	-0.3815	0.4099
42	0.3287	0.3703	0.0969	0.3914	-0.0075	0.2778
43	0.2686	0.7055	0.1279	0.7092	0.3384	0.6567
44	0.2227	0.5825	0.0034	0.6198	-0.0476	0.3878
45	0.3466	0.4252	0.1666	0.4604	-0.1318	0.4362
46	0.0409	0.2398	0.0481	0.2348	-0.1138	0.3500
47	0.1680	0.3732	0.1286	0.3799	-0.0710	0.3749
48	0.1537	0.5075	-0.1374	0.4752	-0.0486	0.3783
49	0.0925	0.3916	0.0584	0.3808	-0.0114	0.4619
50	0.3023	0.3550	0.2784	0.3715	0.2111	0.3195
51	0.0286	0.5781	-0.0602	0.4909	-0.1445	0.4479
52	0.2769	0.2804	0.3025	0.3040	0.2842	0.2943
53	0.4033	0.5179	0.4339	0.4856	0.0972	0.4549
54	0.1982	0.3945	0.1581	0.4159	-0.1708	0.3593
55	0.0601	0.5426	-0.0207	0.4978	0.2265	0.5259
56	-0.3323	0.4904	-0.4291	0.4495	0.0658	0.4787
57	0.3295	0.3195	0.2504	0.3192	-0.1164	0.2948
58	0.4209	0.1883	0.2607	0.2065	0.5545	0.2348
59	-0.3709	0.1884	-0.3286	0.2628	0.4078	0.3030
60	0.2270	0.1961	0.2358	0.2399	-0.0968	0.2183
61	0.2289	0.6367	0.3146	0.5379	-0.1988	0.3929
62	0.1536	0.2778	0.2201	0.2745	-0.0382	0.2481
63	0.2029	0.1965	0.1861	0.2138	0.4981	0.2664
64	0.3390	0.2544	0.3946	0.2651	0.2604	0.2443
65	0.3595	0.4090	0.4012	0.3896	0.0843	0.3415
66	0.2859	0.2564	0.3691	0.2806	0.1256	0.2765
67	0.3757	0.0798	0.3786	0.0788	0.4309	0.0805
68	0.3778	0.2691	0.4119	0.2298	0.2694	0.2410
69	0.3605	0.1963	0.3910	0.1764	0.3915	0.2110
70	0.2839	0.3645	0.2894	0.3319	0.2393	0.3861
71	-0.0270	0.1342	-0.0711	0.1418	-0.1013	0.2202
72	0.1839	0.1631	0.1921	0.1723	0.1481	0.1889
73	0.4040	0.3977	0.3749	0.3922	0.2711	0.3490
74	0.3808	0.1413	0.3597	0.1304	0.2162	0.1424
75	0.3542	0.1252	0.3576	0.1214	0.2690	0.1487
76	0.2817	0.1451	0.2708	0.1396	0.4403	0.1457

Table 2
Mean MPP and Standard Error by MOS and Job Family Configuration Using Standardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
77	0.3710	0.2516	0.3479	0.2488	0.2105	0.2650
78	0.0983	0.2300	0.0315	0.2720	-0.0018	0.3139
79	0.0396	0.3014	0.0149	0.3444	-0.2178	0.4148
80	0.0411	0.1890	-0.0284	0.2669	0.0164	0.3527
81	-0.0301	0.2627	-0.0921	0.3376	0.2238	0.3959
82	0.1023	0.2377	0.0220	0.3038	0.0554	0.2771
83	0.1440	0.2438	0.0056	0.3249	0.2659	0.2724
84	-0.1724	0.2731	-0.0271	0.2782	0.0224	0.2887
85	-0.0467	0.3476	-0.0239	0.3816	-0.2811	0.3790
86	-0.1311	0.4401	-0.1374	0.5357	0.0740	0.6328
87	-0.2688	0.4267	-0.2305	0.4827	-0.0339	0.5121
88	-0.0391	0.3226	-0.2328	0.2727	-0.1474	0.3388
89	-0.0515	0.4473	0.0065	0.4280	0.1445	0.4104
90	0.0081	0.5574	-0.1482	0.4808	-0.3044	0.4756
91	-0.1138	0.6056	-0.1750	0.5348	-0.0395	0.4904
92	0.0362	0.3776	-0.0029	0.3511	-0.0951	0.3254
93	0.0465	0.3221	0.1088	0.3048	0.1569	0.2567
94	0.1662	0.1211	0.1475	0.1205	0.1167	0.1195
95	-0.1164	0.3394	-0.1114	0.3121	-0.1971	0.2574
96	-0.0476	0.1823	-0.0433	0.1807	0.0479	0.2158
97	0.0496	0.2188	0.0522	0.2230	0.1650	0.2262
98	0.1620	0.2340	0.1470	0.2142	0.1472	0.2030
99	0.1553	0.4692	0.1759	0.4514	0.1538	0.4313
100	0.0589	0.4904	0.0577	0.4856	-0.1357	0.3365
101	0.0526	0.1707	-0.0123	0.1583	0.0931	0.1931
102	0.0388	0.4184	0.0063	0.3914	0.1362	0.4367
103	0.0328	0.4144	-0.0111	0.3707	0.1197	0.3836
104	0.0977	0.3453	0.0647	0.3240	0.0420	0.3101
105	0.1282	0.2869	0.0625	0.2906	0.0852	0.3234
106	0.1168	0.4441	0.1141	0.4780	0.0893	0.3914
107	0.0943	0.1812	0.0422	0.1707	0.1602	0.1805
108	-0.2802	0.1162	-0.1590	0.1260	0.0259	0.1865
109	-0.1245	0.3375	-0.0573	0.3680	-0.1875	0.3247
110	-0.4798	0.1178	-0.2738	0.1420	0.5121	0.2211
111	0.0935	0.4405	0.1563	0.4545	0.0068	0.4052
112	-0.1995	0.3154	-0.2670	0.3071	-0.2355	0.3393
113	-0.2982	0.3066	-0.2834	0.3406	0.1070	0.3434
114	0.1505	0.2104	0.2350	0.1994	-0.0024	0.2316

Table 2
Mean MPP and Standard Error by MOS and Job Family Configuration Using Standardized Test Composites

	9		17		150	
	Mean	Std	Mean	Std	Mean	Std
115	0.1675	0.0691	0.2046	0.0763	0.2926	0.0929
116	0.0739	0.2504	0.0887	0.2301	-0.0247	0.1957
117	-0.1758	0.0746	-0.1116	0.1153	0.0012	0.1294
118	-0.0530	0.3800	0.0244	0.3863	0.0397	0.3383
119	0.0598	0.2567	0.0740	0.2661	0.0489	0.2158
120	-0.0941	0.2511	-0.1466	0.2360	-0.1144	0.3440
121	-0.0976	0.5841	-0.0030	0.5975	-0.3409	0.5327
122	-0.0733	0.2067	-0.1064	0.2288	0.2287	0.2023
123	-0.0752	0.4769	-0.0137	0.4812	-0.1315	0.3522
124	-0.1376	0.5535	-0.0763	0.5115	0.0249	0.4653
125	-0.1190	0.5191	-0.0176	0.5292	0.0264	0.5079
126	-0.1901	0.5799	0.0219	0.5502	-0.0570	0.6030
127	-0.1986	0.4761	-0.1150	0.4794	-0.0828	0.4154
128	-0.0700	0.4207	-0.0880	0.4327	-0.3498	0.4065
129	0.0104	0.2845	0.0613	0.3191	-0.2109	0.2495
130	-0.0294	0.0956	0.0605	0.0984	0.1151	0.1077
131	0.1443	0.0991	0.1830	0.0986	0.0304	0.1199
132	0.2379	0.4820	0.2479	0.4880	-0.2534	0.4400
133	0.1138	0.2195	0.2048	0.2328	0.1330	0.2243
134	-0.0269	0.0849	0.0148	0.0868	0.0122	0.1087
135	-0.0968	0.2873	-0.0735	0.2900	-0.2651	0.2382
136	-0.0786	0.4505	-0.1035	0.4752	-0.1617	0.4239
137	-0.1547	0.0830	-0.1657	0.1435	-0.1590	0.1416
138	-0.0817	0.3741	-0.1146	0.3798	-0.3321	0.3678
139	-0.1373	0.2873	-0.1737	0.2979	-0.2191	0.3323
140	-0.3185	0.4141	-0.3983	0.4129	-0.2157	0.5677
141	-0.0340	0.4171	0.1995	0.5144	-0.1206	0.3077
142	-0.0304	0.3477	-0.0972	0.3213	-0.1356	0.3065
143	-0.1528	0.2336	-0.2712	0.2677	-0.3618	0.3274
144	-0.1271	0.1336	-0.2205	0.1621	-0.2901	0.1860
145	-0.1318	0.3163	-0.1692	0.3033	-0.1019	0.2701
146	-0.1847	0.3037	-0.2754	0.2924	-0.3334	0.3569
147	-0.1759	0.3729	0.2739	0.4230	0.0996	0.3162
148	-0.0808	0.2286	-0.3258	0.1988	-0.1562	0.3195
149	-0.1417	0.2586	-0.2767	0.2569	-0.3610	0.2718
150	-0.0342	0.1942	0.0059	0.1987	-0.1397	0.3010

APPENDIX F: DOCUMENTATION OF CUT SCORE EQUATING PROCEDURE, SAS PROGRAM, AND TABLES OF CUT SCORES FOR 17 AND 150 JOB FAMILIES

Cut Score Equating Procedure

Proposed MOS-specific cut scores using alternative composites based on the 17 and 150 job family configuration were computed to be "equivalent" to existing cut scores under the existing LSE composites based on the 9 job family. By "equivalent" we mean that accessions for a given MOS based on the alternative composite and proposed cut score for the MOS will have the same mean predicted performance (MPP) as accessions based on the current composite and existing cut score for the same MOS.

Generally, varying criterion validities can be expected between the existing and alternative composites. When the alternative composite has higher validity compared to the existing composite, a cut score that is lower than the existing value can produce the same level of MPP. Thus, the benefit of improved composite validity is achieved through large pool of eligible applicants (i.e., higher selection ratio). When the alternative composite has lower validity, we can compensate for its lower predictive power by setting a higher cut score that will produce the same level of MPP. This is achieved at the expense of a smaller eligible pool of higher average quality applicants than the existing pool. These ideas underlie the cut score equating procedure describe below.

Denote the current composite for the *m*th MOS by X_o, with validity R_o and cut score currently set at C_o, and the alternative composite by X_n, with validity R_n. Also denote the common mean and standard deviation under the current and alternative composites (using 9, 17 or 150 job families) by constants $\mu_x = 100$ and $\sigma_x = 20$. Using these notations the MPP under the current and alternative composites and cut scores can be written as

$$MPP_o = R_o \times \left(\frac{\mu_{X>C_o} - \mu_x}{\sigma_x} \right)$$

$$MPP_n = R_n \times \left(\frac{\mu_{X>C_n} - \mu_x}{\sigma_x} \right)$$

The terms inside the parentheses are simply the truncated mean of the composite above the respective cut scores in standardized form.

Under the equivalent cut score condition, we have MPP_n equals MPP_o, where the latter is a known value and the former involves the unknown cut score C_n of interest. For this equality to be useful in solving for the equivalent alternative cut score, first we need to expand the truncated means of the composites X_o and X_n in the MPP expressions above as function of the composite mean and variance. Assuming a normal distribution for the composite in the applicant population and using standard mathematical results (e.g., Greene 1997), we obtain

$$\mu_{X>C_o} = \mu_x + \sigma_x \times \lambda\left(\frac{C_o - \mu_x}{\sigma_x}\right)$$

$$\mu_{X>C_n} = \mu_x + \sigma_x \times \lambda\left(\frac{C_n - \mu_x}{\sigma_x}\right)$$

The "hazard" function λ is given by the expression below in terms of the standard normal density $\phi(z)$ and cumulative distribution $\Phi(z)$.

$$\lambda(z) = \frac{\phi(z)}{1 - \Phi(z)}$$

Setting MPP under current and alternative composites and cut scores equal, and after some algebraic manipulations to separate known and unknown terms on either side of the equation, we obtain

$$\left(\frac{R_o}{R_n}\right)\lambda\left(\frac{C_o - \mu_x}{\sigma_x}\right) = \lambda\left(\frac{C_n - \mu_x}{\sigma_x}\right)$$

Thus, to obtain the unknown equivalent cut score Cn, we solve for the zero of the non-linear equation

$$0 = \lambda\left(\frac{C_n - \mu_x}{\sigma_x}\right) - L$$

where the constant L is simply the known value of the entire expression on the left-hand side of the preceding equality relationship. The solution to this problem was carried out using the Newton iterative method. The SAS program implementation of the entire cutscore equating procedure appears on the next page.

```
/**************************************************************************

Data for Input to Cut Score Equating Problem
--------------------------------------------------------------------------
MOS-JF-CutScore Configuration:
(1) mos = MOS ID
(2) mosnumid = numeric ID (1,2,...,155)
(3) jf0103_9 jf0103_17 jf0103_150 = numerice ID for JF9, JF17, and JF150 as
of JAN03
(4) c0 = cut score based on JF9 ocmposite
--------------------------------------------------------------------------
Input Data to Cut Score Equating Problem:
(1) zc0 =  standardized cut score on JF9
(2) q0 = selection ration based on c0 and JF9 composite (1-probnorm(zc0))
(3) r0 = validity of JF9 composite
(4) pp0 = predicted performance based on c0 and JF9 composite of MOS
(5) r1 = validity of JF17 composite
Output Data from Cut Score Equating Problem:
(6) zc1 = standardized cut score on JF17 composite
(7) q1 = selection ratio on JF17 composite and cut score
(8) c1 = cut score on JF17 composite that gives the same predicted
performance
**************************************************************************/

/**************************************************************************

Cut Score Equating Calculations
NOTE: MOS in JAN03 file that not found in the SQT data are excluded. The
ASVAB validities
for these MOS are not available.
**************************************************************************/

%let dataMosCsConfig=lcs.mosCurCS;
%let dataRXY155=lvalid.YouthValid;
%let dataRXY9=lvalid.JF9YouthValid;

%macro CutScoreEquate(dataRXY17,dataYouthCov,dataCSsoln,AltNumJF);
%let  PI=3.14159265;
proc iml;

/**************************************************************************
  Newton procedure for solving root of LAMBDA function
**************************************************************************/
  start F_LAMBDA(z);
    phiz = exp(0.5*(-z##2))/sqrt(2*&PI); lambda = phiz/(1-probnorm(z));
    return(lambda);
  finish F_LAMBDA;
  start DF_LAMBDA(z);
    phiz = exp(0.5*(-z##2))/sqrt(2*&PI); dphiz = -z*phiz; pnormz =
probnorm(z);
    dlambda = ( dphiz*(1-pnormz) + phiz##2 ) / (1-pnormz)##2;
    return(dlambda);
  finish DF_LAMBDA;
  start SOLVE_LAMBDA(lambdaConstant,initZ,epsZ, maxIter,opt);
    if (opt[1]) then
      print lambdaConstant[label="lambdaConstant"
format=10.8],initZ[label="initZ" format=10.8];
```

```
    z0=initZ;  minDiff=epsZ; zDiff=1; maxiter=20;
    do iter=1 to maxiter while(zDiff>minDiff);
      z1 = z0 - (F_LAMBDA(z0)-lambdaConstant)/DF_LAMBDA(z0);
      zDiff = abs(z1-z0);
      z0 = z1;
      if (opt[2]) then
        print iter[label="iter" format=3.0] z0[label="ZSOLN" format=10.8]
              zDiff[label="zDiff" format=10.8];
    end;
    return(z0);
  finish SOLVE_LAMBDA;
  /* Testing Code
  zcSOLN = 1.987654;
  lambdaLHS = F_LAMBDA(zcSOLN);
  zcSolved = SOLVE_LAMBDA(lambdaLHS,0,1e-6,20);
  print zcSolved[label="zcSolved" format=10.8];
  */

/*****************************************************************************
  Read MOS-JF-CutScore Configuration Data
*****************************************************************************/
  use &dataMosCsConfig;
  read all var{mosnumid} into mosNumID;
  read all var{jf0103_9} into JF9;
  read all var{cutscore} into JF9CS;
  read all var{jf0103_&AltNumJF} into JFalt;
  close &dataMosCsConfig;
  *print mosNumID JF9 JFalt JF9CS;

/*****************************************************************************
  Read MOS155, JF9, JFalt Youth ASVAB validities, and Youth ASVAB covariance
matrix
*****************************************************************************/
  TestNames = {GS AR AS MK MC EI VE};
  use &dataRXY155;
  read all var(TestNames) into rxy155;
  close &dataRXY155;
  use &dataRXY9;
  read all var(TestNames) into rxy9;
  close &dataRXY9;
  use &dataRXY17;
  read all var(TestNames) into rxy17;
  close &dataRXY17;
  use &dataYouthCov;
  read all var(TestNames) where(names?TestNames)  into cxxYouth;
  close &dataYouthCov;
  *print rxy155 rxy9 rxy17 rxxYouth;
```

```
/*************************************************************************
  Quantities for Current JF9 composite that are available or readily computed:
  (1) zc0 =  standardized cut score on JF9
  (2) q0 = selection ration based on c0 and JF9 composite (1-probnorm(zc0))
  (3) r0 = validity of JF9 composite
  (4) pp0 = predicted performance based on c0 and JF9 composite of MOS
  -----------------------------------------------------------------------
  Quantities for "New" JFalt composite that are available or readily computed:
  Known quantities from "new" JFalt Composite:
  (5) r1 = validity of JFalt composite
  Quantities for "New" JFalt composite that are caculated through cut score
equating:
  (6) zc1 = standardized cut score on JFalt composite
  (7) q1 = selection ratio on JFalt composite and cut score
  (8) c1 = cut score on JFalt composite that gives the same predicted
performance
*************************************************************************/
  meanComp=100; stdComp=20;
  stdXX = sqrt(vecdiag(cxxYouth));
  rxxYouth = diag(1/stdXX)*cxxYouth*diag(1/stdXX);
  numMos = nrow(mosNumID);
  zc0=repeat(0,numMos); q0=repeat(0,numMos); r0=repeat(0,numMos);
pp0=repeat(0,numMos);
  zc1=repeat(0,numMos); q1=repeat(0,numMos); r1=repeat(0,numMos);
JFaltCS=repeat(0,numMos);

  do idxMos=1 to numMos;

    zc0[idxMos] = (JF9CS[idxMos]-meanComp)/stdComp;
    q0[idxMos] = 1 - probnorm(zc0[idxMos]);
    r0[idxMos] = sqrt(rxy155[idxMos,]*inv(rxxYouth)*t(rxy9[JF9[idxMos],]));
    pp0[idxMos] = r0[idxMos]*(meanComp + stdComp*F_LAMBDA(zc0[idxMos]));

    r1[idxMos] =
sqrt(rxy155[idxMos,]*inv(rxxYouth)*t(rxy17[JFalt[idxMos],]));
    lambdaLHS = (r0[idxMos]/r1[idxMos])*F_LAMBDA(zc0[idxMos]);
    zc1[idxMos] = SOLVE_LAMBDA(lambdaLHS,zc0[idxMos],1e-6,20,{1 1});
    q1[idxMos] = 1 - probnorm(zc1[idxMos]);
    JFaltCS[idxMos] = meanComp + stdComp*zc1[idxMos];

  end;

  matOut = mosNumID || JF9CS || zc0 || q0 || r0 || r1 || zc1 || q1 ||
JFaltCS;
  create &dataCSsoln var{mosNumID JF9CS zc0 q0 r0 r1 zc1 q1 JF&AltNumJF.CS};
  append from matOut;
  close &dataCSsoln;

quit;
run;

%mend;

options mprint=1;

%CutScoreEquate(lvalid.JF17YouthValid,lvalid.PopCovYouth,lcs.csSolnFixPP_JF17
,17);
%CutScoreEquate(lvalid.Jf150youthvalid,lvalid.PopCovYouth,lcs.csSolnFixPP_JF1
50,150);
```

Table 1
New and Old Cut Scores and Qualification Rates by MOS for 17 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF17CS
1	87	-0.65	0.742153889	0.528374924	0.50900736	-0.615296654	0.730820587	87.69406692
2	87	-0.65	0.742153889	0.602825356	0.580085098	-0.614256995	0.730477242	87.71486011
3	87	-0.65	0.742153889	0.590782909	0.568950082	-0.615003971	0.730723951	87.69992059
4	87	-0.65	0.742153889	0.540846301	0.520561268	-0.614468113	0.730546981	87.71063775
5	87	-0.65	0.742153889	0.593138316	0.630243661	-0.705168449	0.759647293	85.89663103
6	87	-0.65	0.742153889	0.59534116	0.632041602	-0.704398351	0.759407634	85.91203298
8	91	-0.45	0.67364478	0.624690167	0.624690167	-0.45	0.67364478	91
9	91	-0.45	0.67364478	0.569657011	0.569657011	-0.45	0.67364478	91
10	91	-0.45	0.67364478	0.66029159	0.66029159	-0.45	0.67364478	91
11	91	-0.45	0.67364478	0.662381536	0.662381536	-0.45	0.67364478	91
12	95	-0.25	0.598706326	0.663324105	0.663324105	-0.25	0.598706326	95
14	98	-0.1	0.539827837	0.648680415	0.648680415	-0.1	0.539827837	98
22	87	-0.65	0.742153889	0.605869684	0.643843124	-0.705268283	0.759678353	85.89463434
24	87	-0.65	0.742153889	0.620224189	0.66069355	-0.707436999	0.760352524	85.85126002
26	92	-0.4	0.655421742	0.689912396	0.704544844	-0.421706029	0.663380199	91.56587941
29	102	0.1	0.460172163	0.5921857	0.590830448	0.103006391	0.458978949	102.0601278
33	98	-0.1	0.539827837	0.669540892	0.669540892	-0.1	0.539827837	98
35	89	-0.55	0.708840313	0.610008827	0.604585071	-0.541342954	0.705864391	89.17314091
37	107	0.35	0.363169349	0.701824913	0.70111151	0.351488998	0.362610762	107.02978
39	98	-0.1	0.539827837	0.62863297	0.62863297	-0.1	0.539827837	98
40	116	0.8	0.211855399	0.665774129	0.663984154	0.804749204	0.21048221	116.0949841
42	102	0.1	0.460172163	0.667514629	0.678873927	0.077982631	0.468920935	101.5596526
43	107	0.35	0.363169349	0.668178174	0.678647341	0.327356329	0.371699196	106.5471266
44	102	0.1	0.460172163	0.685673394	0.694533268	0.083228333	0.466834992	101.6645667
45	98	-0.1	0.539827837	0.647524571	0.657463354	-0.118158605	0.547029006	97.6368279
48	88	-0.6	0.725746882	0.72296745	0.756598437	-0.642488143	0.739721857	87.15023714
49	97	-0.15	0.559617692	0.735289835	0.769205125	-0.202108333	0.580083983	95.95783334
50	88	-0.6	0.725746882	0.600596715	0.628873893	-0.642986236	0.739883484	87.14027529
51	93	-0.35	0.636830651	0.640425362	0.672029756	-0.400670342	0.655668575	91.98659317
52	97	-0.15	0.559617692	0.694022416	0.690916029	-0.144746289	0.557544405	97.10507422
53	97	-0.15	0.559617692	0.71979739	0.754128421	-0.203820078	0.580752949	95.92359843
56	93	-0.35	0.636830651	0.735260276	0.770509576	-0.399274616	0.655154566	92.01450767
58	88	-0.6	0.725746882	0.701389192	0.670573296	-0.557137068	0.711283108	88.85725864
59	88	-0.6	0.725746882	0.686933742	0.657246038	-0.557860406	0.711530145	88.84279188
60	88	-0.6	0.725746882	0.656507343	0.627799471	-0.557346082	0.711354502	88.85307835
61	93	-0.35	0.636830651	0.728627437	0.721701283	-0.33980615	0.632998742	93.20387701
62	102	0.1	0.460172163	0.60610754	0.621789864	0.06675345	0.473388991	101.335069
63	97	-0.15	0.559617692	0.680025098	0.712658695	-0.204139466	0.580877743	95.91721068
64	97	-0.15	0.559617692	0.709182712	0.743268433	-0.204220618	0.58090945	95.91558764
65	92	-0.4	0.655421742	0.746809578	0.76818708	-0.42913755	0.666088437	91.41724899
66	96	-0.2	0.579259709	0.664528937	0.646312705	-0.167998996	0.566707966	96.64002007
67	104	0.2	0.420740291	0.724644707	0.69259301	0.262882774	0.396320467	105.2576555
70	87	-0.65	0.742153889	0.70000591	0.693833377	-0.641822058	0.739505637	87.16355884
71	88	-0.6	0.725746882	0.740144864	0.707759246	-0.557318261	0.711344999	88.85363479

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 17 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF17CS = New AA Cut Score (17 JF Level).

Table 1 (cont'd)
New and Old Cut Scores and Qualification Rates by MOS for 17 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF17CS
72	88	-0.6	0.725746882	0.705386736	0.674175432	-0.556822855	0.711175766	88.86354291
73	88	-0.6	0.725746882	0.641538019	0.614321678	-0.558659727	0.711803015	88.82680545
74	87	-0.65	0.742153889	0.713812452	0.713335988	-0.649384606	0.741955094	87.01230788
75	97	-0.15	0.559617692	0.764372563	0.764445456	-0.15011154	0.559661692	96.9977692
76	97	-0.15	0.559617692	0.792072668	0.791226469	-0.148749321	0.559124279	97.02501359
77	97	-0.15	0.559617692	0.750551996	0.750970597	-0.150652098	0.559874919	96.98695804
78	87	-0.65	0.742153889	0.676698726	0.678247461	-0.652105523	0.742833449	86.95788953
79	87	-0.65	0.742153889	0.64366095	0.645477037	-0.652594721	0.742991205	86.94810558
81	97	-0.15	0.559617692	0.728881979	0.726486185	-0.146145427	0.558096707	97.07709145
82	102	0.1	0.460172163	0.69485919	0.693992438	0.101637274	0.459522296	102.0327455
83	87	-0.65	0.742153889	0.750439786	0.749837689	-0.649260225	0.741914905	87.01479551
84	97	-0.15	0.559617692	0.691086211	0.690103098	-0.148334177	0.558960478	97.03331646
85	102	0.1	0.460172163	0.701452311	0.729104488	0.049870208	0.480112909	100.9974042
86	97	-0.15	0.559617692	0.70697104	0.703505772	-0.14424477	0.557346405	97.1151046
87	102	0.1	0.460172163	0.717587198	0.707256229	0.119096867	0.452599306	102.3819373
88	102	0.1	0.460172163	0.627235496	0.62447777	0.105785404	0.457876309	102.1157081
89	102	0.1	0.460172163	0.711505261	0.71170251	0.099636559	0.460316434	101.9927312
90	102	0.1	0.460172163	0.672302894	0.672714302	0.099197971	0.460490543	101.9839594
91	102	0.1	0.460172163	0.738440547	0.743938095	0.09029515	0.464026337	101.805903
92	102	0.1	0.460172163	0.784300107	0.782027342	0.10380861	0.458660617	102.0761722
93	102	0.1	0.460172163	0.784078298	0.786851176	0.095375689	0.462008213	101.9075138
94	102	0.1	0.460172163	0.71409059	0.729673218	0.071872091	0.47135185	101.4374418
95	93	-0.35	0.636830651	0.721649898	0.739391879	-0.375701582	0.646430619	92.48596837
97	93	-0.35	0.636830651	0.637569126	0.65821653	-0.383662211	0.649385588	92.32675579
99	107	0.35	0.363169349	0.423410229	0.411633457	0.391656386	0.34765606	107.8331277
101	92	-0.4	0.655421742	0.698706419	0.699100407	-0.400585981	0.655637516	91.98828038
105	92	-0.4	0.655421742	0.65003742	0.650371295	-0.400533773	0.655618293	91.98932455
106	103	0.15	0.440382308	0.664871044	0.66403832	0.15168111	0.439719228	103.0336222
107	96	-0.2	0.579259709	0.668700721	0.678896435	-0.217222651	0.585982583	95.65554698
108	92	-0.4	0.655421742	0.65279443	0.642282328	-0.383053994	0.649160135	92.33892013
112	103	0.15	0.440382308	0.689781704	0.687766474	0.153926677	0.438833775	103.0785335
117	88	-0.6	0.725746882	0.686601595	0.688882708	-0.603129218	0.726788635	87.93741565
118	88	-0.6	0.725746882	0.707626076	0.675890021	-0.556215773	0.710968321	88.87568455
119	85	-0.75	0.773372648	0.658118465	0.674468889	-0.771426019	0.779772771	84.57147962
120	92	-0.4	0.655421742	0.666742561	0.688851107	-0.433641766	0.6677257	91.32716468
121	88	-0.6	0.725746882	0.733410493	0.701855772	-0.55805483	0.711596528	88.83890339
122	85	-0.75	0.773372648	0.709052039	0.709052039	-0.75	0.773372648	85
123	97	-0.15	0.559617692	0.650034124	0.645589902	-0.141960302	0.556444319	97.16079395
124	107	0.35	0.363169349	0.723223681	0.676987953	0.448751292	0.32680554	108.9750258
125	92	-0.4	0.655421742	0.723462278	0.688546032	-0.347932303	0.636054488	93.04135393
126	92	-0.4	0.655421742	0.731579645	0.692634942	-0.342343802	0.633953912	93.15312396
129	107	0.35	0.363169349	0.713964828	0.676729247	0.429741524	0.333691837	108.5948305
130	95	-0.25	0.598706326	0.703489738	0.703489738	-0.25	0.598706326	95
131	107	0.35	0.363169349	0.740458173	0.701597213	0.430267425	0.33350056	108.6053485
132	92	-0.4	0.655421742	0.661641669	0.627934561	-0.344922685	0.634923752	93.10154631

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 17 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF17CS = New AA Cut Score (17 JF Level).

Table 1 (cont'd)

New and Old Cut Scores and Qualification Rates by MOS for 17 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF17CS
133	96	-0.2	0.579259709	0.703459776	0.668330344	-0.140644133	0.555924459	97.18711734
134	102	0.1	0.460172163	0.540006869	0.505735404	0.187672118	0.425566844	103.7534424
135	92	-0.4	0.655421742	0.678738208	0.639929164	-0.33787774	0.632272338	93.24244521
137	92	-0.4	0.655421742	0.723581145	0.715971111	-0.38897919	0.65135423	92.22041621
138	85	-0.75	0.773372648	0.697797652	0.697797652	-0.75	0.773372648	85
139	88	-0.6	0.725746882	0.674647315	0.64509594	-0.557270966	0.711328845	88.85458069
140	88	-0.6	0.725746882	0.667530862	0.639479244	-0.559062609	0.711940504	88.81874782
141	92	-0.4	0.655421742	0.721646975	0.706723333	-0.378161655	0.647344746	92.43676689
142	96	-0.2	0.579259709	0.737485532	0.757922758	-0.231011139	0.591346926	95.37977722
143	93	-0.35	0.636830651	0.721584522	0.718489973	-0.345419177	0.635110369	93.09161645
144	92	-0.4	0.655421742	0.704051744	0.722670289	-0.42696104	0.665296148	91.46077919
145	92	-0.4	0.655421742	0.68449826	0.702443632	-0.426733006	0.665213096	91.46533987
146	96	-0.2	0.579259709	0.696044518	0.715326945	-0.231001086	0.591343021	95.37997827
147	102	0.1	0.460172163	0.633256782	0.6489369	0.068155869	0.472830779	101.3631174
148	102	0.1	0.460172163	0.63754039	0.658876113	0.057249181	0.477173351	101.1449836
149	93	-0.35	0.636830651	0.657476775	0.658242868	-0.351239503	0.637295662	92.97520993
150	102	0.1	0.460172163	0.697719236	0.725191857	0.049927471	0.480090093	100.9985494
151	92	-0.4	0.655421742	0.713548551	0.740726056	-0.438504926	0.66948985	91.22990148
152	102	0.1	0.460172163	0.704493117	0.729707014	0.054361242	0.478323679	101.0872248
154	92	-0.4	0.655421742	0.691700773	0.717427129	-0.437624481	0.669170739	91.24751038

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 17 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF17CS = New AA Cut Score (17 JF Level).

Table 2

New and Old Cut Scores and Qualification Rates by MOS for 150 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF150CS
1	87	-0.65	0.742153889	0.528374924	0.4752681	-0.549999321	0.70884008	89.00001359
2	87	-0.65	0.742153889	0.602825356	0.59534875	-0.638467207	0.738415203	87.23065586
3	87	-0.65	0.742153889	0.590782909	0.582748295	-0.63734273	0.738049188	87.2531454
4	87	-0.65	0.742153889	0.540846301	0.49605518	-0.568756024	0.715239139	88.62487953
5	87	-0.65	0.742153889	0.593138316	0.583612345	-0.635025874	0.73729423	87.29948252
6	87	-0.65	0.742153889	0.59534116	0.593876042	-0.647728155	0.741419605	87.0454369
8	91	-0.45	0.67364478	0.624690167	0.583837466	-0.380196228	0.648100121	92.39607544
9	91	-0.45	0.67364478	0.569657011	0.569932557	-0.450490801	0.673821707	90.99018398
10	91	-0.45	0.67364478	0.66029159	0.649234221	-0.432787255	0.667415333	91.34425489
11	91	-0.45	0.67364478	0.662381536	0.653318653	-0.435969035	0.668570402	91.2806193
12	95	-0.25	0.598706326	0.663324105	0.60326404	-0.141336758	0.556198044	97.17326484
14	98	-0.1	0.539827837	0.648680415	0.580543473	0.037074543	0.485212785	100.7414909
22	87	-0.65	0.742153889	0.605869684	0.608148781	-0.653457006	0.743269151	86.93085989
24	87	-0.65	0.742153889	0.620224189	0.634552351	-0.670939019	0.748870311	86.58121961
26	92	-0.4	0.655421742	0.689912396	0.613927381	-0.275045676	0.608359427	94.49908647
29	102	0.1	0.460172163	0.5921857	0.497792982	0.340002407	0.366927357	106.8000481
33	98	-0.1	0.539827837	0.669540892	0.617647499	-0.001212665	0.500483783	99.97574669
35	89	-0.55	0.708840313	0.610008827	0.547886292	-0.443413884	0.671266802	91.13172231
37	107	0.35	0.363169349	0.701824913	0.582664361	0.639346246	0.261298855	112.7869249
39	98	-0.1	0.539827837	0.62863297	0.589447296	-0.021550936	0.508596914	99.56898129
40	116	0.8	0.211855399	0.665774129	0.562044096	1.117181308	0.131958405	122.3436262
42	102	0.1	0.460172163	0.667514629	0.600896509	0.242279127	0.404281943	104.8455825
43	107	0.35	0.363169349	0.668178174	0.568036453	0.600490253	0.274089777	112.0098051
44	102	0.1	0.460172163	0.685673394	0.586686166	0.314314816	0.376640973	106.2862963
45	98	-0.1	0.539827837	0.647524571	0.570754226	0.056562875	0.477446704	101.1312575
48	88	-0.6	0.725746882	0.72296745	0.667234012	-0.522832647	0.699454641	89.54334707
49	97	-0.15	0.559617692	0.735289835	0.672379244	-0.042761147	0.517054032	99.14477707
50	88	-0.6	0.725746882	0.600596715	0.563205817	-0.538401086	0.704849912	89.23197828
51	93	-0.35	0.636830651	0.640425362	0.546217486	-0.173423593	0.568840759	96.53152813
52	97	-0.15	0.559617692	0.694022416	0.570228887	0.092882317	0.462998527	101.8576463
53	97	-0.15	0.559617692	0.71979739	0.661440112	-0.048765357	0.519446855	99.02469287
56	93	-0.35	0.636830651	0.735260276	0.660442092	-0.232534139	0.591938413	95.34931722
58	88	-0.6	0.725746882	0.701389192	0.625608476	-0.489125181	0.687623462	90.21749639
59	88	-0.6	0.725746882	0.686933742	0.620497789	-0.50166076	0.692046914	89.9667848
60	88	-0.6	0.725746882	0.656507343	0.543248141	-0.41301169	0.660200975	91.73976621
61	93	-0.35	0.636830651	0.728627437	0.6627156	-0.246554585	0.597373522	95.0689083
62	102	0.1	0.460172163	0.60610754	0.545345245	0.242977269	0.404011503	104.8595454
63	97	-0.15	0.559617692	0.680025098	0.60253374	-0.003643765	0.501453649	99.9271247
64	97	-0.15	0.559617692	0.709182712	0.647485687	-0.04082538	0.516282447	99.1834924
65	92	-0.4	0.655421742	0.746809578	0.71585551	-0.355522	0.638900717	92.88955999
66	96	-0.2	0.579259709	0.664528937	0.60542832	-0.090832655	0.536187219	98.18334689
67	104	0.2	0.420740291	0.724644707	0.637454212	0.3828734	0.350906817	107.657468
70	87	-0.65	0.742153889	0.70000591	0.656400152	-0.589860491	0.722357908	88.20279019
71	88	-0.6	0.725746882	0.740144864	0.665260459	-0.496752332	0.690318143	90.06495335

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 150 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF150CS = New AA Cut Score (150 JF Level).

Table 2 (cont'd)

New and Old Cut Scores and Qualification Rates by MOS for 150 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF150CS
72	88	-0.6	0.725746882	0.705386736	0.640135999	-0.506259999	0.69366293	89.87480002
73	88	-0.6	0.725746882	0.641538019	0.585418578	-0.511710424	0.695573155	89.76579151
74	87	-0.65	0.742153889	0.713812452	0.664743539	-0.583302578	0.720155186	88.33394843
75	97	-0.15	0.559617692	0.764372563	0.655285599	0.038037174	0.484829021	100.7607435
76	97	-0.15	0.559617692	0.792072668	0.702993657	-0.005745797	0.502292229	99.88508405
77	97	-0.15	0.559617692	0.750551996	0.638492143	0.047897481	0.480898974	100.9579496
78	87	-0.65	0.742153889	0.676698726	0.577052888	-0.497725101	0.690661093	90.04549799
79	87	-0.65	0.742153889	0.64366095	0.554044258	-0.506994237	0.693920569	89.86011526
81	97	-0.15	0.559617692	0.728881979	0.62497767	0.037797144	0.484924711	100.7559429
82	102	0.1	0.460172163	0.69485919	0.586903212	0.333037117	0.369553133	106.6607423
83	87	-0.65	0.742153889	0.750439786	0.705636543	-0.592476656	0.723234276	88.15046688
84	97	-0.15	0.559617692	0.691086211	0.601728946	0.018326624	0.492689144	100.3665325
85	102	0.1	0.460172163	0.701452311	0.631130181	0.242980631	0.404010201	104.8596126
86	97	-0.15	0.559617692	0.70697104	0.61064814	0.028474678	0.488641782	100.5694936
87	102	0.1	0.460172163	0.717587198	0.619901888	0.300551548	0.381878242	106.011031
88	102	0.1	0.460172163	0.627235496	0.538203859	0.310244414	0.378187549	106.2048883
89	102	0.1	0.460172163	0.711505261	0.599025674	0.33773355	0.367781995	106.754671
90	102	0.1	0.460172163	0.672302894	0.578822271	0.305399418	0.380030982	106.1079884
91	102	0.1	0.460172163	0.738440547	0.520344156	0.612226785	0.270193861	112.2445357
92	102	0.1	0.460172163	0.784300107	0.649859209	0.361083378	0.359018559	107.2216676
93	102	0.1	0.460172163	0.784078298	0.674131718	0.307366949	0.379282041	106.147339
94	102	0.1	0.460172163	0.71409059	0.650047849	0.226724563	0.410318963	104.5344913
95	93	-0.35	0.636830651	0.721649898	0.636957623	-0.212721965	0.584228083	95.7455607
97	93	-0.35	0.636830651	0.637569126	0.587380383	-0.260847518	0.602894951	94.78304965
99	107	0.35	0.363169349	0.423410229	0.356023067	0.618407143	0.268153495	112.3681429
101	92	-0.4	0.655421742	0.698706419	0.59428135	-0.224598824	0.58885431	95.50802353
105	92	-0.4	0.655421742	0.65003742	0.551062966	-0.220864184	0.587400907	95.58271633
106	103	0.15	0.440382308	0.664871044	0.577736298	0.346638438	0.364431483	106.9327688
107	96	-0.2	0.579259709	0.668700721	0.567639178	-0.004122272	0.501644544	99.91755457
108	92	-0.4	0.655421742	0.65279443	0.576894781	-0.267404109	0.605420982	94.65191783
112	103	0.15	0.440382308	0.689781704	0.585243736	0.381790438	0.351308406	107.6358088
117	88	-0.6	0.725746882	0.686601595	0.686187842	-0.599430793	0.725557176	88.01138415
118	88	-0.6	0.725746882	0.707626076	0.609817015	-0.454554038	0.675284946	90.90891924
119	85	-0.75	0.773372648	0.658118465	0.529017661	-0.548807564	0.708431241	89.02384872
120	92	-0.4	0.655421742	0.666742561	0.629788933	-0.339867233	0.633021743	93.20265535
121	88	-0.6	0.725746882	0.733410493	0.603876116	-0.407871695	0.658316063	91.8425661
122	85	-0.75	0.773372648	0.709052039	0.662762631	-0.689873342	0.754863079	86.20253316
123	97	-0.15	0.559617692	0.650034124	0.503509664	0.171302032	0.431993142	103.4260406
124	107	0.35	0.363169349	0.723223681	0.636415672	0.545018727	0.292870319	110.9003745
125	92	-0.4	0.655421742	0.723462278	0.634518572	-0.258995779	0.602180751	94.82008442
126	92	-0.4	0.655421742	0.731579645	0.588233432	-0.160144163	0.563616244	96.79711674
129	107	0.35	0.363169349	0.713964828	0.506940659	0.912092839	0.180859924	118.2418568
130	95	-0.25	0.598706326	0.703489738	0.618740187	-0.101679041	0.540494281	97.96641918
131	107	0.35	0.363169349	0.740458173	0.657309146	0.531148154	0.297658059	110.6229631
132	92	-0.4	0.655421742	0.661641669	0.602385987	-0.300117834	0.617956362	93.99764332

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 150 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF150CS = New AA Cut Score (150 JF Level).

Table 2 (cont'd)

New and Old Cut Scores and Qualification Rates by MOS for 150 Job Families

MOS	JF9CS	ZC0	Q0	R0	R1	ZC1	Q1	JF150CS
133	96	-0.2	0.579259709	0.703459776	0.639431045	-0.088078269	0.535092766	98.23843463
134	102	0.1	0.460172163	0.540006869	0.467668426	0.296957005	0.383249667	105.9391401
135	92	-0.4	0.655421742	0.678738208	0.591156765	-0.251231385	0.59918239	94.9753723
137	92	-0.4	0.655421742	0.723581145	0.65403854	-0.292231207	0.614945073	94.15537587
138	85	-0.75	0.773372648	0.697797652	0.667701054	-0.71093473	0.761437658	85.7813054
139	88	-0.6	0.725746882	0.674647315	0.603321784	-0.491712326	0.688538638	90.16575348
140	88	-0.6	0.725746882	0.667530862	0.532245086	-0.374310745	0.645913431	92.5137851
141	92	-0.4	0.655421742	0.721646975	0.621424046	-0.238510865	0.594257555	95.2297827
142	96	-0.2	0.579259709	0.737485532	0.651422748	-0.05330761	0.521256592	98.9338478
143	93	-0.35	0.636830651	0.721584522	0.652192158	-0.239506072	0.594643406	95.20987857
144	92	-0.4	0.655421742	0.704051744	0.650429566	-0.315982375	0.623992057	93.68035251
145	92	-0.4	0.655421742	0.68449826	0.612574471	-0.281294117	0.610757589	94.37411766
146	96	-0.2	0.579259709	0.696044518	0.596800715	-0.016621562	0.506630739	99.66756876
147	102	0.1	0.460172163	0.633256782	0.541478552	0.315267912	0.376279123	106.3053582
148	102	0.1	0.460172163	0.63754039	0.590475826	0.202886347	0.419611933	104.0577269
149	93	-0.35	0.636830651	0.657476775	0.604700706	-0.258974552	0.602172562	94.82050897
150	102	0.1	0.460172163	0.697719236	0.619541292	0.261492955	0.396856191	105.2298591
151	92	-0.4	0.655421742	0.713548551	0.629789208	-0.266005378	0.604882467	94.67989243
152	102	0.1	0.460172163	0.704493117	0.617336211	0.280199843	0.389662094	105.6039969
154	92	-0.4	0.655421742	0.691700773	0.629281011	-0.299300219	0.617644506	94.01399561

Note. MOS = MOS ID Number; JF9CS = Old AA Cut Score (9 JF Level); ZCO = Standardized Old AA Cut Score; Q0 = Qualification Rate Under Old Cut Score; R0 = Validity of 9 JF-Level AA Composite; R1 = Validity of 150 JF Level AA Composite; ZC1 = Standardized New AA Cut Score; Q1 = Qualification Rate Using New Cut Score; JF150CS = New AA Cut Score (150 JF Level).